AGENCY FOR INTERNATIONAL DEVELOPMENT
WASHINGTON, D. C. 20523

BIBLIOGRAPHIC INPUT SHEET

FOR AID USE ONLY

BATCH #14

1. SUBJECT CLASSIFICATION	A. PRIMARY Agriculture	AE10-0000-G704
	B. SECONDARY Agricultural economics--Korea Rep.	

2. TITLE AND SUBTITLE
Development of a grain management simulation model

3. AUTHOR(S)
Gibson, F.J.

4. DOCUMENT DATE	5. NUMBER OF PAGES	6. ARC NUMBER
1973	103p.	ARC

7. REFERENCE ORGANIZATION NAME AND ADDRESS
Mich. State

8. SUPPLEMENTARY NOTES (Sponsoring Organization, Publishers, Availability)
(In KASSIM working paper no.73-1)

9. ABSTRACT

10. CONTROL NUMBER	11. PRICE OF DOCUMENT
PN-RAA-748	

12. DESCRIPTORS	13. PROJECT NUMBER
Computer programs Grain crops Korea Rep. Simulation	14. CONTRACT NUMBER CSD-2975 Res. 15. TYPE OF DOCUMENT

KASSIM WORKING PAPER

No. 73-1

DEVELOPMENT OF A GRAIN MANAGEMENT SIMULATION MODEL

(To Be Revised)

by

F.J. Gibson

January 1, 1973

(Latest Revision 3/15/73)

FOREWORD

This research study is based on the original conceptualization of a grain management system introduced in KASSIM Working Paper 72-1, "Description of a Preliminary Grain Management System Model", authored jointly by T.J. Manetsch and S. G. Kim.

The present paper is being written to serve as an ongoing <u>working draft</u> for the development of the KASSIM grain management model. Although it may seem mired down with detail, one should keep in mind that it is meant to serve two purposes.

First, the paper is meant to document some of the <u>ideas</u> being considered in the development of the KASS model, thereby opening the way for criticism and suggestions at an early stage of development. Documentation usually comes in the final stages of system development, after the model is conceptualized, computerized and running. And it is normally not until the model has been documented that meaningful dialogue can be exchanged between model designers, who may tend to know more about techniques than existing economic phenomena, and model users, who may tend to know more about the latter.

Secondly, the paper should act as a communication link between the writer and computer programmers. It is a means of getting some thoughts, ideas and suggestions down in balck and white which may be of help when developing the associated computer program. It also frees the writer to become more involved in other aspects of the system development b. turning some of the burdensome and time-consuming tasks of actual simulation programming and debugging over to the computer programmers.

It is the writer's intention to make this paper as useful as possible — both for the development of the associated computer simulation programs, and also for the final documentation of the model. For this reason, equations may be seen written in two forms: (1) in a general time domain form which is more applicable to final documentation of the model, and (2) in actual FORTRAN form which may help clarify certain ideas to the programmers. Sometimes what is represented by a single time domain equation may require a series of FORTRAN statements. It is not the writer's intention to dictate exactly how the programming should be done. In fact, the programmers will most likely have several "better ways" to do things — this is fine and welcome. Again, the reason for including a few FORTRAN statements is merely to improve communications. As the corresponding computer simulation program is developed and proves to be functioning properly, more refined versions of this paper will see a disappearance of programming discussions and more emphasis on the theoretical concepts behind the equations.

Some topics and subtopics appear in this paper with very little or no discussion. These may represent areas which are not yet fully developed or else bottlenecks which need more thought.

They also may represent areas which the writer has chosen not to discuss at this time. Whatever the case, they serve as "flags" for more work and later supplements or revisions.

TABLE OF CONTENTS

	Page
I. GENERAL DESCRIPTION OF THE GM SYSTEM	5
II. GOVERNMENT GM SUBSECTOR MODEL	10
III. PRIVATE MARKETING (PM) SUBSECTOR MODEL	10
A. Ordinary PM Model Structure (w/o Speculation).	10
1. General Description	10
2. Component Equations	10
a. PM Inventories	10
b. PM Expenditures	14
c. PM Revenue	16
d. PM Profit (on current sales)	18
B. Speculative PM Behavioral Model Structure . .	20
1. General Model Description	21
2. Projection Mechanisms	26
a. Price Projections	26
1) A Stochastic Model for Projecting Producer Prices	28
a) Long Term Price Trend (PTL). .	30
b) Deviations from the PTL (DPTL)	34
c) Average Deviations from the PTL (ADPTL).	34

TABLE OF CONTENTS (con't) Page

d) Autocorrelation and Standard Deviation of Price Deviation from PTL (ACDP & SDP) 36

2) Smoothing the Projected Price Profiles 38

a) Polynomial Functional Form . . 39

b) Fourier Series Model 41

3) Projecting Consumer Prices 43

b. Profitability and Profit Projections. . 44

1) Speculative Profitability on Current Purchases (SP_i) 44

2) Speculative Profitability Profile (SPP_i) 45

3) Speculative Profit Profile (SFF_i) . 47

c. Urban Demand Projections 49

1) Initial Approach - Use Behavioral Response Function Used in Simulation 49

2) Alternative Approach 50

3. Decision Mechanism 51

a. PM Inventory Capacity Allocation (Short-Run) 51

1) The Problem 51

2) A Solution 51

b. PM Inventory Capacity Adjustment (Long-Run) 54

TABLE OF CONTENTS (con't) Page

c. PM Inventory (Stockpile) Adjustment . . . 57

1) Comment on Dynamic Programming . . 57

2) PM Speculative Demands and Marketings 57

3) Use of the DELDT Routine in Generating PM Demands and Marketings . . . 62

4. Self-Adapting Mechanism 65

a. Performance Criteria 65

b. Correction Factors 69

5. Information Storage and Retrieval Mechanism 70

a. Price Data Adjustments 70

b. Updating Historical Data with Cyclic Boxcar Routines 72

c. Application of GASP Utility Routines. . 73

C. General Operating Pattern of the PM Subsector Simulation Model 74

D. Modifications in Existing KASSIM Components . . 82

E. Further Development 84

APPENDIX A (PM Subsector Variables). 88

APPENDIX B (Adjusted Coefficients for Seasonal Response) . 91

DEVELOPMENT OF A GRAIN MANAGEMENT SIMULATION MODEL

I. GENERAL DESCRIPTION OF THE GM SYSTEM

II. GOVERNMENT GM SUBSECTOR

At the present stage in development the government GM subsector is adequately documented in KASSIM Working Paper 72-1. As model development progresses and the government subsector undergoes substantial modifications, it will be redocumented under this section of later revisions to this working paper.

An activity analysis of the current government subsector model is given in Figure II-1. This analysis groups all the variables used in the present version of the government subsector into inputs, outputs, or parameters and defines the exact units of measure for each variable. The relationships between these variables are depicted by the causal map of Figure II-2.

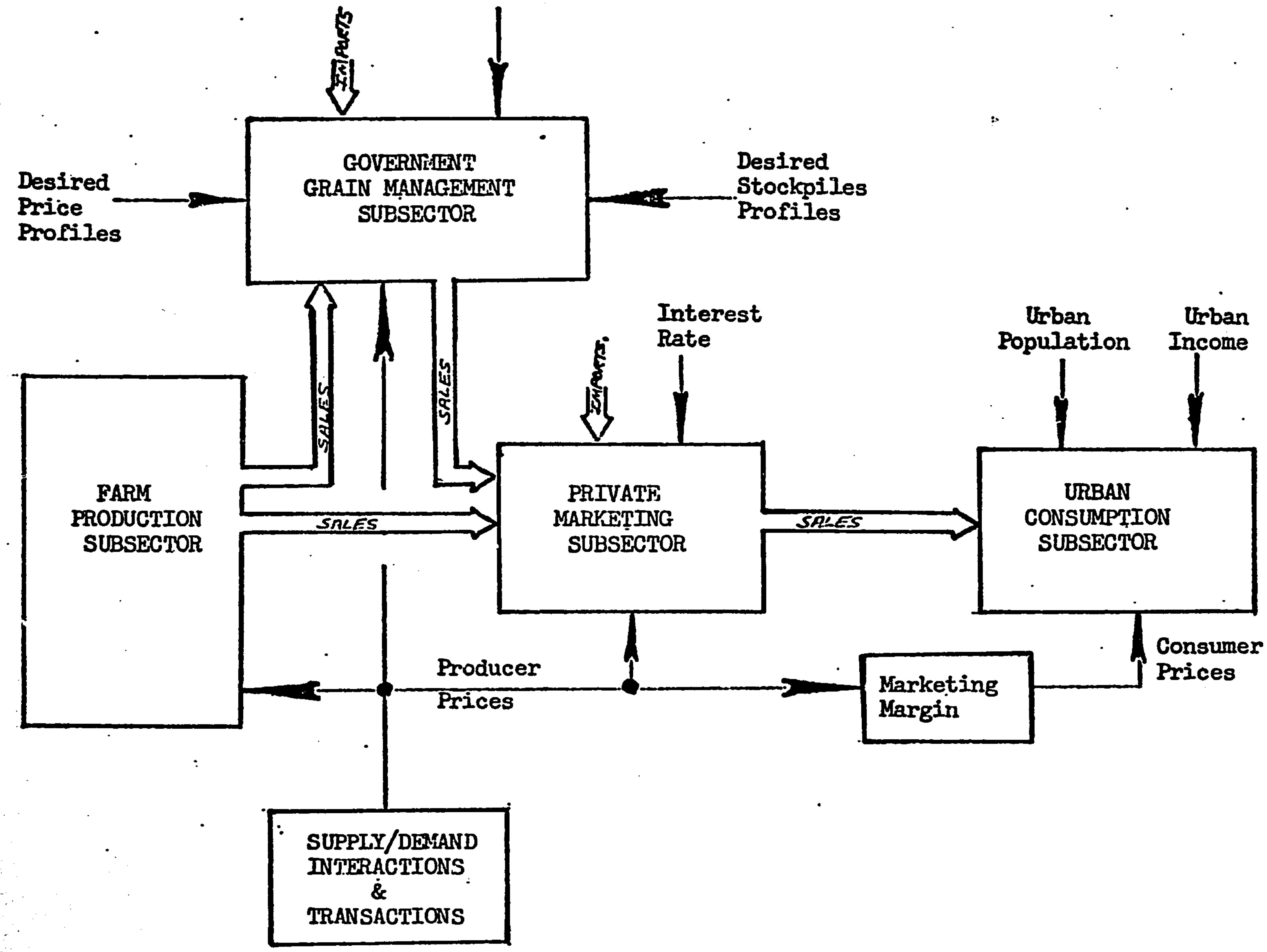
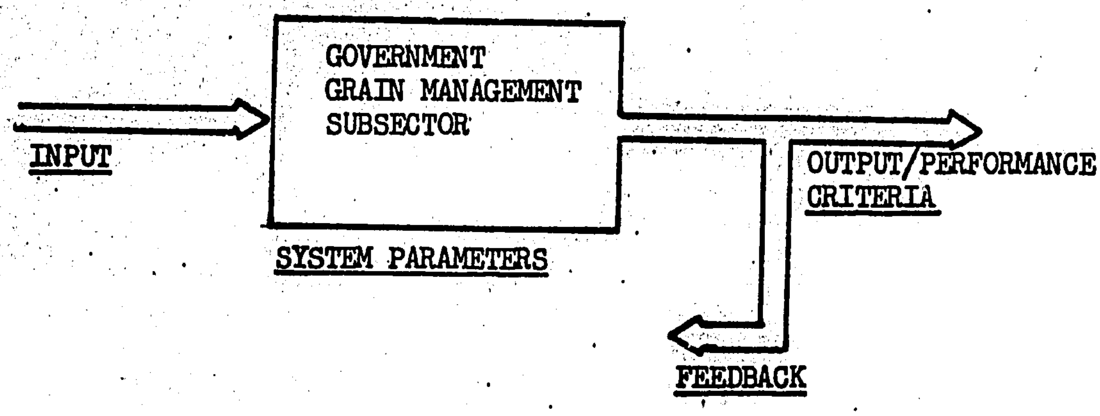


Figure 1. Grain Management Program Simulation Model
(General Outline)

Figure II - 1 — Activity Analysis of Government Subsector



INPUT

Prices

Government Buying Price	PB_i — W/MT
Government Selling Price	PS_i — W/MT
Desired Producer Price	PD_i — W/MT
Actual Producer Prices	P_i — W/MT
World Prices (Delivered to Ports)	$PWLD_i$ — \$/MT

Inventory

Desired Inventory Level	$GINVD_i$ — MT
Desired Inventory Capacity	CAPIND — MT

Revenue Transfers

From Bank of Korea	RBOK — W/yr
From Other Government Sources	OGREV — W/yr

Other Inputs

Average Urban Demand	$DEMUA_i$ — MT/yr

SYSTEM PARAMETERS

Price Control (Feedback)

Proportional Gain	$G3_i$ — %
Derivative Gain	$G4_i$ — %

Figure II - 1 — con't

Inventory Level Control (Feedback)	
Proportional Gain	$G1_i$ — %
Derivative Gain	$G2_i$ — %
Storage Loss Rate	$STLOSS_i$ — %/yr
Inventory Capacity Control (Feedback)	
Proportional Gain	C3 — %
Average Costs	
Selling Cost	CS_i — W/MT
Buying Cost	CB_i — W/MT
Holding Cost	$C1_i$ — W/MT-yr
Inventory Overhead Cost	C2 — W/MT-yr
Managerial, Administration Cost	C4 — W/yr
Import Loans	
Proportion of Government Imports Paid in Cash	$PCTCSH_i$ — %
Repayment Period Interest	RINT — %/yr
Grace Period Interest	GINT — %/yr
Delays	
Loan Grace Period	
Average	$DELGP_i$ — yrs
Probability Distribution	KGR_i — no units
Loan Repayment Period	
Average	$DELRP_i$ — yrs
Probability Distribution	KRP_i — no units

Figure II - 1 — con't

Import Payment Period	
Average	$DELIWT_i$ — yrs
Probability Distribution	KWT_i — no units
Warehouse Acquisition Period	
Average	DELWA — yrs
Probability Distribution	KWAR — no units
Importation Period	
Average	$DELIMP_i$ — yrs
Probability Distribution	$KIMP_i$ — no units
Other Parameters	
W - $ Conversion	WOND — W/$
[illegible]PUT/PERFORMANCE CRITERIA	
Government Storage	
Commodity Inventory Level	$GINV_i$ — MT
Storage Losses	$GSLOSS_i$ — MT/yr
Total FG Stockpile	TGINV — MT
Government Cost of Holding Inventory	CHI_i — W/yr
Inventory Capacity	
Government Warehouse Capacity	CAPINV — MT
Excess Inventory Capacity	EXICAP — MT
Warehouse Acquisition Orders	RWAREI — MT/yr
Actual Warehouse Acquisition Rate	RWAREO — MT/yr
Current Capacity Under Constructor (or being acquisitioned)	WUC — MT
Overhead Cost of GM Program	COH — W/yr

Figure II-1 — con't

Imports	
Import Orders	$RIMPI_i$ — MT/yr
Imports in Pipeline	$PIPIMP_i$ — MT
Import Deliveries	$GIMP_i$ — MT/yr
Import Loans	
Import Loans Entering Grace Period	$RGRACI_i$ — \$/yr
Import Loans Leaving Grace Period	$RGRACO_i$ — \$/yr
Import Loans Entering Repayment Period	$RREPYI_i$ — \$/yr
Import Loan Repayment Rate	$RREPYO_i$ — \$/yr
Total Outstanding Loans	TOL_i — \$
Loan Payments to Principle and Interest	$PPAI_i$ — W/yr
Sales and Revenue	
Government Sales/Purchases (unconstrained)	Al_i — MT/yr
Government Sales/Purchases (constrained)	$PSLS_i$ — MT/yr
Revenue from Sales/Purchases	$GOVREV_i$ — W/yr
Net Revenue Flow	REV_i — W/yr
Total Net Revenue Flow	TREV — W/yr
Accounting and Finance	
Commodity Cash Balances	$CBAL_i$ — W
Total Cash Balance	$TCBAL_i$ — W
Total GM Balance	TGMBAL — W
Foreign Exchange Deficit (Paid in Cash)	$FOREXC_i$ — \$/yr
Transfer of Funds for Import Payments	$WTIMP_i$ — W/yr
Won Value of Imports Paid in Cash	$CIMPW_i$ — W
Won Value of Total Imports	$TWCIMP_i$ — W

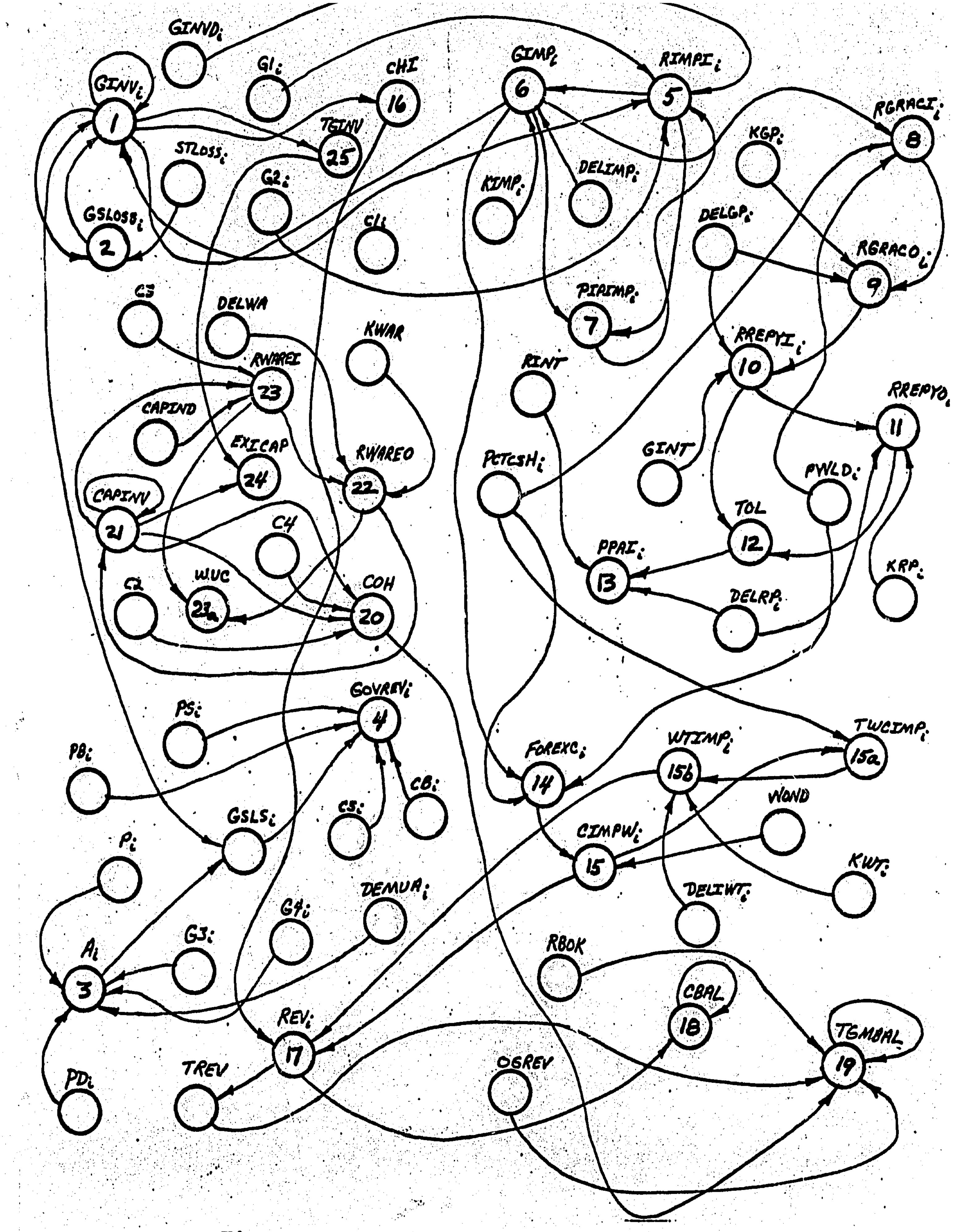


Figure VI-2 CAUSAL MAP OF GM SUBSECTOR MODEL

III. PRIVATE MARKETING (PM) SUBSECTOR SIMULATION MODEL

A. ORDINARY PM MODEL STRUCTURE (W/O SPECULATION)

1. GENERAL DESCRIPTION

Some of the input-output relationships for the ordinary private marketing subsector of the GM model are shown in the activity analysis of Figure A1(1). This may aid the reader in following the discussion of the system diagram of Figure A1(2) which follows.

As shown in Figure A1(2), the private marketing system's demand for grain is composed of two components: an ordinary demand to satisfy urban consumption requirements (QP_i), and a speculative demand of its own to adjust existing inventory levels ($PDAI_i$). The ordinary demand function will be discussed in this section, whereas the speculative demand function will be discussed in section B below.

2. COMPONENT EQUATIONS

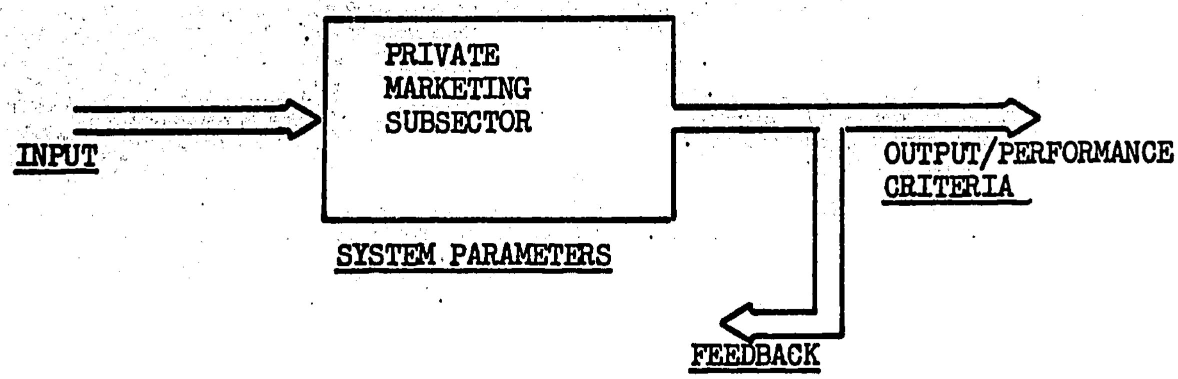
a. PM INVENTORY

Equation (1) expresses the dynamics of PM inventory stocks over time for all commodities considered in the GM system. The index i indicates commodity in all equations this paper.

$$PINV_i(t+DT) = PINV_i(t) + DT * [PPUR_i(t) * (1-PLOSS_i) - QP_i(t)] \quad (1)$$

FJG
5/10/73

Figure A1(1) — Activity Analysis of PM Subsector



INPUT

Consumer Demand	Q_i — MT/yr
PM Purchases	$PPUR_i$ — MT/yr
Producer Prices	P_i — W/MT
Consumer Prices	CPU_i — W/MT

SYSTEM PARAMETERS

Average Costs

Storage and Handling Costs	$A1_i$ — W/MT-yr
Storage Capacity Costs	$A2_i$ — W/MT-yr
Selling Cost	$A3_i$ — W/MT
Acquisition Cost	$A4_i$ — W/MT

Market

Proportion Direct Farm Sales	PDF — %
Marketing Margin	MM_i — %
Private Marketing Losses	$PMLOSS_i$ — %/yr
Interest Rate	INT — %/yr

Figure A1(1) — con't

OUTPUT/PERFORMANCE CRITERIA

PM Storage

PM Inventory Levels	$PINV_i$ — MT
Total PM Inventory Level	TPINV — MT
PM Inventory Capacity	PCAP — MT

Costs

Average Variable Costs of Holding Inventory	$AVCHPI_i$ — W/MT-yr
Variable Costs of Holding Inventory	$VCHPI_i$ — W/yr
Fixed Costs of Holding Inventory	$FCHPI_i$ — W/yr
Total Costs of Holding Inventory	$TCHPI_i$ — W/yr

Expenditures

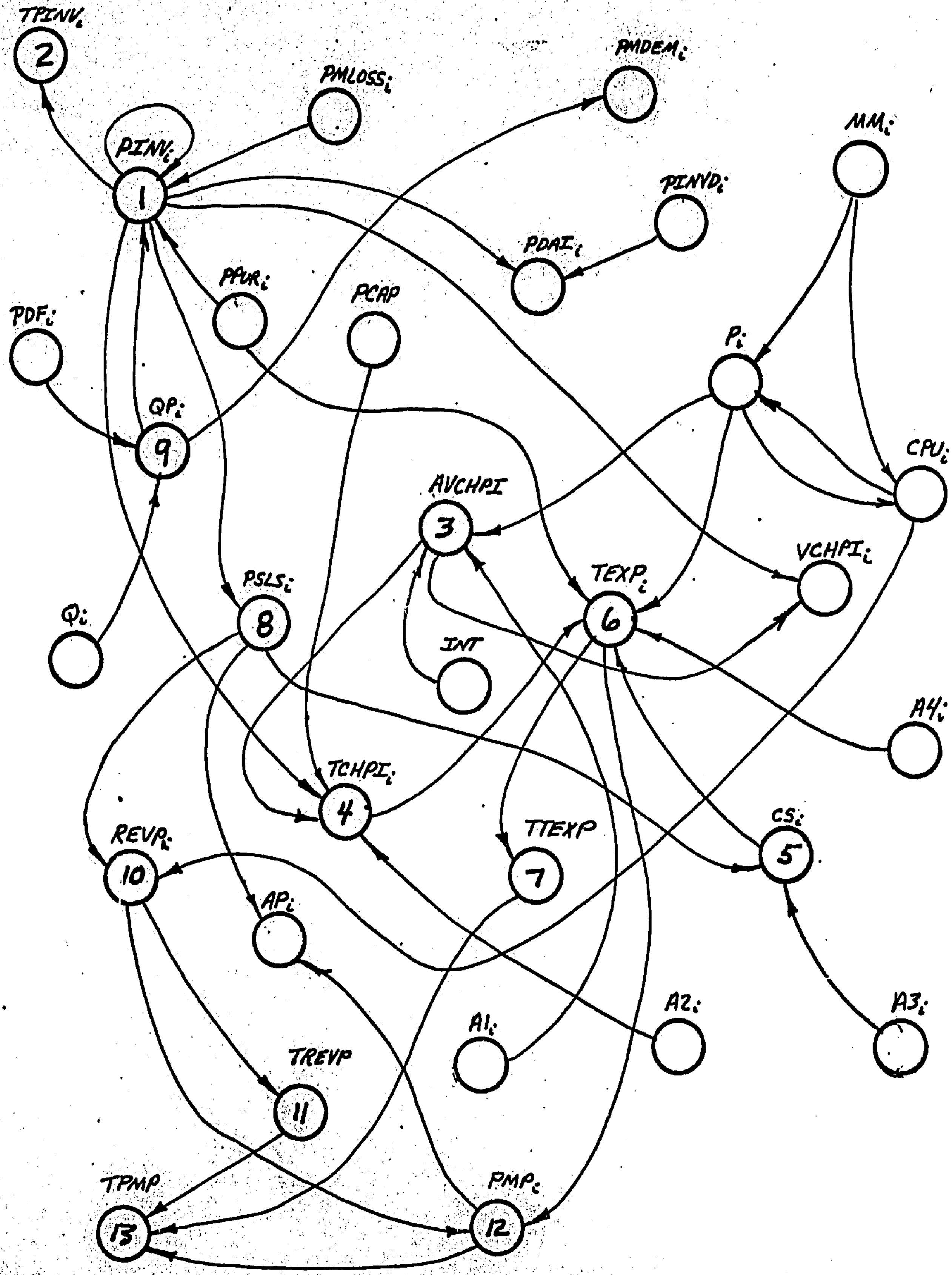
Total PM Commodity Expenditures	$TEXP_i$ — W/yr
Total PM Expenditures	TTEXP — W/yr

Demands

Effective Urban Demand	QP_i — MT/yr
PM Demand to Adjust Inventory	$PDAI_i$ — MT/yr
Total PM Demand	$PMDEM_i$ — MT/yr

Sales, Revenues and Profits

PM Commodity Sales	$PSLS_i$ — MT/yr
PM Commodity Revenue	$REVP_i$ — W/yr
Total PM Revenue	TREVP — W/yr
PM Commodity Profits	PMP_i — W/yr
Total PM Profit	TPMP — W/yr
Current PM Profitability on Sales	AP_i — W/MT-yr



CAUSAL MAP OF PM SUBSECTOR MODEL

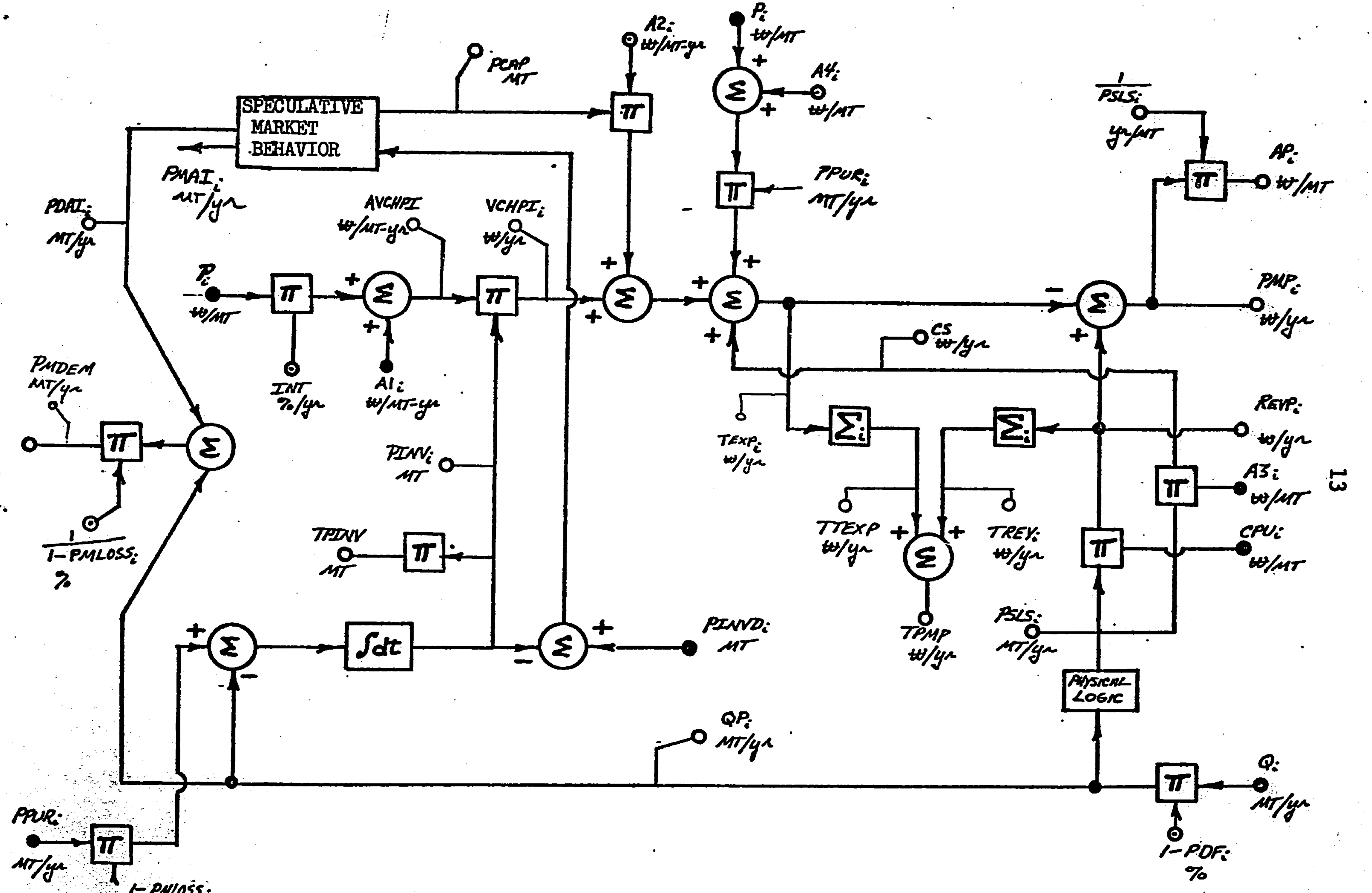


Figure A1(2) — Private Marketing Subsector System Diagram

where:

PINV = PM stockpiles — MT

PPUR = PM purchases — MT/yr

PMLOSS = PM losses — %/yr[1]

QP = urban consumer demand felt by PM — MT/yr

DT = basic time increment used in the model (normally .025 yrs) — yrs

Aggregate stockpiles are calculated from the following summation:

$$TPINV\ (t) = \sum_{i=1}^{NC} PINV_i(t) \tag{2}$$

b. PM EXPENDITURES

The average variable costs associated with holding private stocks are given by

$$AVCHPI_i(t) = INT(t) * P_i(t) + A1_i \tag{3}$$

where:

AVCHPI = average variable cost of holding private stocks — W/MT-yr

PINV = level of PM stockpiles — MT

INT = interest rate — percent/yr

P = purchasing price — W/MT

A1 = storage and handling cost — W/MT-yr

The average fixed cost associated with maintaining

---

[1] The percentage symbol "%" in this paper is used to depict "proportion of the whole."

present storage capacity is given by $A2_i$ -- W/MT-yr. As actual PM storage capacity changes, we might expect that this average fixed cost also to change. For the present, however, we will assume that $A2_i$ will remain constant.

The total cost associated with holding a certain level of private stocks consists of the variable costs (W/yr) of holding this amount, plus the fixed cost (W/yr) of maintaining the present storage capacity.

$$TCHPI_i(t) = AVCHPI_i(t) * PINV_i(t) + A2_i * PCAP(T) \tag{4}$$

where:

TCHPI = total cost of holding PM inventory — W/yr

AVCHPI = average variable costs of holding PM inventory — W/MT-yr

PINV = level PM stockpiles — MT

A2 = average fixed cost of storage capacity — W/MT-yr

PCAP = PM storage capacity — MT

There is a cost associated with selling commodities in the private market,

$$CS_i = A3_i * PSLS_i(t) \tag{5}$$

where:

CS = cost of selling in private market — W/yr

A3 = average cost of selling in PM — W/MT

PSLS = private marketing sales — MT/yr

The total (commodity specific) expenditure by the PM subsector is now represented by the total cost of processing the stocks from the producer plus costs of holding the stocks plus the costs of selling to the consumer.

$$TEXP_i(t) = PPUR_i(t) * [P_i(t) + A4_i] + TCHPI_i(t) + CS_i(t) \qquad (6)$$

where:

TEXP = total expenditure on PM supply — W/yr

PPUR = private marketing purchases — MT/yr

P = purchasing price from farmers — W/MT

A4 = acquisition cost of products — W/MT

TCHPI = total cost of hold private inventory — W/yr

Total expenditures for all commodities handled by the PM subsector are given by

$$TTEXP(t) = \sum_{i=1}^{NC} TEXP_i(t) \qquad (7)$$

c. PM REVENUE

It is assumed for the time being that all non-agricultural consumption demand is supplied through the private marketing subsector. In reality, of course, a small percentage of nonagricultural consumption supply bypasses conventional marketing channels. These transactions, for example, may consist of gifts or sales to relatives in the cities or sales to consumers on the way to market. The proportion of these types of transactions relative to total sales in urban areas cannot be accurately estimated at present, since it is largely unrecorded and oftentimes kept confidential. Later sensitively analyses will help determine if more attention should be given to further research in determining this actual proportion. At present, however, this proportion is assumed zero. Private marketing sales are therefore given by

$$PSLS_i(t) = QP_i(t) \qquad \text{if } PINV_i > 0$$
$$= 0 \qquad \text{if } PINV_i = 0 \tag{8}$$

and $QP_i(t)$ in (t) is given by

$$QP_i(t) = (1-PDF_i) * Q_i(t) \tag{9}$$

where:

PSLS = private marketing sales, constrained by current stocks — MT/yr

CPU = urban consumer price — W/MT

QP = nonagricultural consumption supplied by the PM subsector — MT/yr

PDF = proportion of nonagricultural consumption supplied directly by farmers (presently set to zero) — ratio

Q_i = total nonagricultural demand — MT/yr

The revenue received by the private marketing subsector is given by

$$REVP_i(t) = CPU_i(t) * PSLS_i(t) \tag{10}$$

where:

REVP = revenues flow to private marketing subsector — W/yr

CPU = urban consumer prices — W/MT

PSLS = private marketing sales — MT/yr

Total revenue from all commodities handled by the PM subsector is given by

$$TREVP(t) = \sum_{i=1}^{NC} REVP_i(t) \quad (11)$$

d. PM PROFIT (ON CURRENT SALES)

PM profit is now given by the simple relationship

$$PMP_i(t) = REVP_i(t) - TEXP_i(t) \quad (12)$$

Total profit from all commodities handled by the PM subsector is given

$$TPMP_i(t) = \sum_{i=1}^{NC} PMP_i(t) = TREVP(t) - TTEXP(t) \quad (13)$$

where:

PMP_i = PM profit on current sales — W/yr

REVP = revenue flow PM subsector — W/yr

TEXP = total expenditures by PM subsector — W/yr

TPMP = total profit of PM subsector — W/yr

TREVP = total revenue from all commodities — W/yr

TTEXP = total costs all commodities — W/yr

The current profitability of handling commodity i in the PM subsector is given by the following equation.

$$AP_i(t) = PMP_i(t)/PSLS_i(t) \tag{14}$$

where:

AP = current profitability of commodity i — W/MT

PMP = see above — W/yr

PSLS = private marketing sales — MT/yr

B. SPECULATIVE PM BEHAVIOR MODEL STRUCTURE

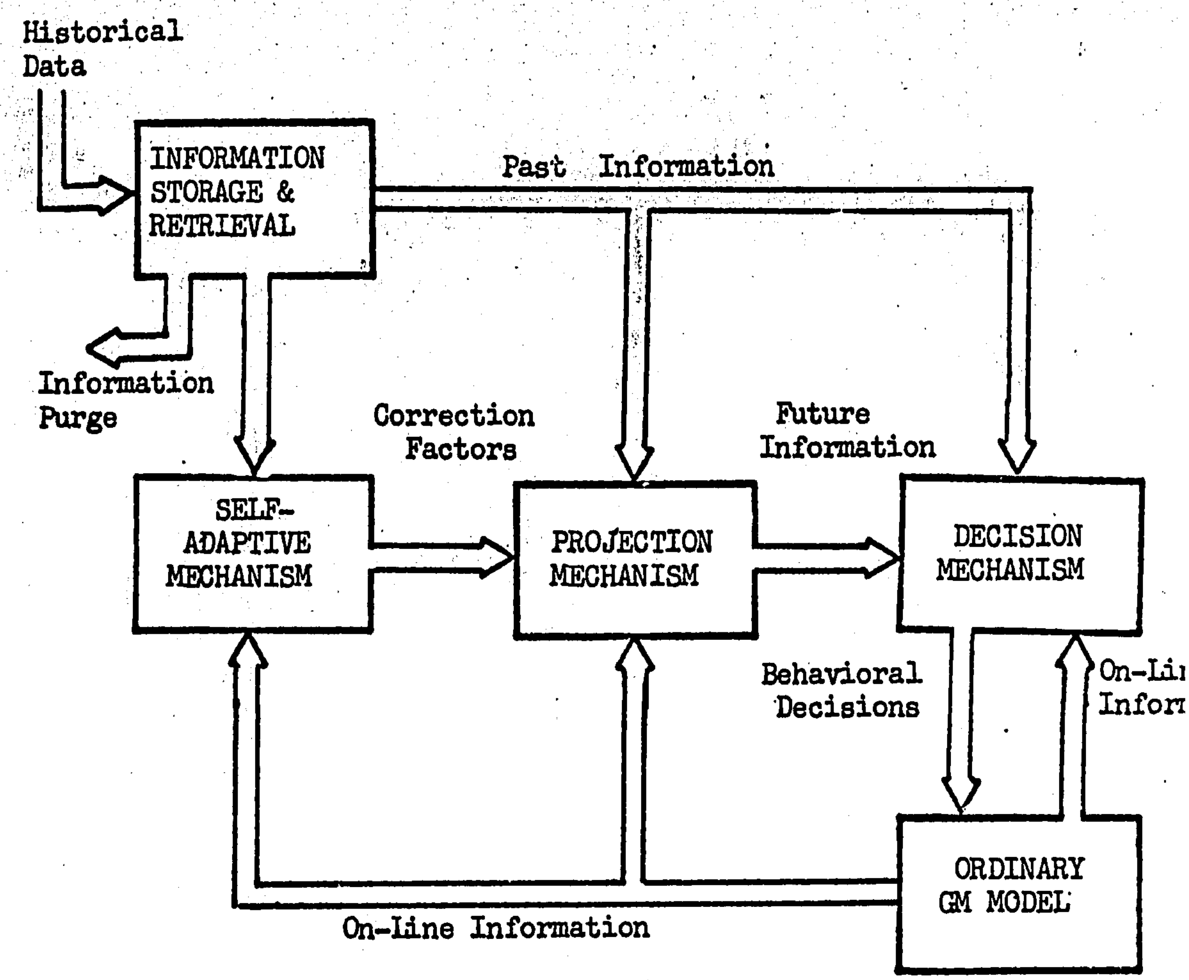
There are two principle means of showing a profit in the private marketing system. First is the ordinary marketing margin between existing farm and retail prices. In the present model this markup is considered to be a constant percentage of farm prices, adequate to cover the costs of grain handling and also provide for a normal profit for the private marketing industry. The second and more risky means of profit is to take advantage of the general change in price levels due to changes in supply and demand between the time grain handlers purchase their products from the producer and sell them to the consumer. Those who engage in and survive this latter activity of buying, holding, and selling grains at a higher profit due to seasonal price changes must follow an intelligent rational behavior pattern. In the aggregate, these market speculators must tend to buy more, allowing inventory levels to grow during low price periods; and buy less, allowing inventory levels to deplete during high price periods. As seasonal price fluctuations become less and less drastic, remaining market speculators must adjust their inventories with critical precision. In order to develop an accurate simulation model of the private marketing subsector, it is necessary that we attempt to simulate the behavior patterns of these keen market speculators.

1. GENERAL MODEL DESCRIPTION

Some of the important information flows and relationships are depicted in the activity analysis of Figure B1(1). It is in this subcomponent of the GM model that speculative decisions are made. These decisions consist of more than the simple logic needed to prevent sales from a nonexisting inventory or to preclude the "stretching" of existing inventory capacities. Projections of future marketing information must be performed in this component. Behavior decisions such as the timing and level of purchases and marketings are determined as a result of these projections.

The projection mechanisms must be self-adaptive to changing situations through time. Paramaters which are used to characterize the original projection mechanism will be based on recent historical data furnished at the beginning of the simulation run. As the simulation progresses through "time," and the results of various policy inputs are felt throughout the entire system, the original parameters can become outdated and may no longer be valid for accurate prediction. Original historical data is therefore progressively replaced by actual output from the simulation run. Projection mechanism parameters are periodically recalculated throughout the run based on this most recent "historical information." The performance or accuracy of the

Figure B1(1) — Activity Analysis of Speculative Market Behavioral Model



<u>INPUTS</u>

<u>Historical Data</u>

Producer Prices	$PHIST_i$ — W/MT

<u>On-Line Information from Ordinary PM Model</u>

PM Purchases	$PPUR_i$ — MT/yr
PM inventory Levels	$PINV_i$ — MT
PM Inventory Capacity	$PCAP_i$ — MT
Producer Prices	P_i — W/MT
Urban Demands	Q_i — MT/yr

<u>SYSTEM PARAMETERS</u>

<u>Urban Demand Projection Parameters</u>

Regression Coefficients	SUD_i — MT/yr

Figure B1(1) — con't

Price Projection Parameters

Regression Coefficients	PTL_i — W/yr
Average Deviations from PTL	$ADPTL_i$ — W/yr
Autocorrelations	$ACDP_i$ — no units
Standard Deviations	SDP_i — W/MT

Inventory Adjustment Parameters

Stock Level Adjustment - Proportional Gain	$G5_i$ — %/yr
Inventory Capacity Adjustment - Proportional Gain	$G6_i$ — %/yr

INTERNAL VARIABLES/OUTPUT/PERFORMANCE CRITERIA

Projections

Speculative Price Time Series	PPS_i — W/MT
Speculative Profitability Profiles	SPP_i — W/MT
Projected Urban Demand Time Series	SUD_i — MT/yr
Speculative Profit Profile	SFF_i — W/yr
Optimal Holding Times	OTH_i — yrs

Self-Adaptive Correction Factors

New Price Projection Parameters (see parameters)

PTL_i

$ADPTL_i$

$ACDP_i$

SDP_i

Price Projection Correction Factors	PCF_i — %
Urban Demand Correction Factors	QCF_i — %

Figure B1(1) — con't

Speculative Decision Behavior

PM Demand to Adjust Inventory	$PDAI_i$ — MT/yr
PM Desired Inventory Capacity	DPCAP — MT
PM Marketings	$PMAI_i$ — MT/yr

projection mechanisms can be measured. Past projections are compared with actual realized values. These errors are then utilized to (hopefully) improve future projections.

The PM behavioral model will serve as the nerve center for the PM subsector component of the foodgrain (FG) management model. Decisions regarding the amount and timing of purchases and sales of foodgrain will come from this mechanism. Priority decisions which determine how available storage capacity will be allocated among competing commodities will be made here. Decisions which will determine the growth or decline of total storage capacity will also be made. All decisions (except those reflecting government decrees) are made with one objective: to maximize PM subsector profits. Whether these decisions do maximize profits or even assure the survival of the PM subsector will depend on several things: (1) how sharp market speculators (modelled) are in projecting future market information, (2) how "predictable" future market information actually is, and (3) the degree to which PM speculators are restrained from engaging in profit maximizing activities.

Quite a bit of consideration has been given to this portion of the FG model which attempts to simulate the behavioral patterns of intelligent human beings. One might wonder if the small box in the upper left portion of Figure A1(2) deserves this much attention at this stage. However, many of the features conceptualized and developed for this PM behavioral mechanism can be utilized in refining other components, of the KASSIM model.

2. PROJECTION MECHANISM

a. PRICE PROJECTIONS

A glance at some recent statistical data on rice prices (see Figure B1(1)) indicates that the seasonal price fluctuations are becoming smaller in recent years. These decreases in the seasonal price fluctuations are a result of the ROK Government's increasing involvement in food grain management programs. As price fluctuations continue to decrease, the success (and survival) of market speculators will be determined by how well they can anticipate future selling prices, $PSS_i(t+t_h)$. In modeling speculative behavior, one of the initial problems facing us is to generate realistically anticipated price patterns. In essense, the model must "intelligently" guess, based on past data (and its own output to date), future expected input prices. Its behavior will then be affected by the values of these future anticipated price patterns. Since the response of the model will depend on future (anticipated) values of inputs (prices), the model can be classified as a form of pseudo-noncausal or anticipatory system.

It is reasonable to assume that those remaining in the business of grain storage and price speculation will be those who have successfully anticipated future price patterns. Since it is our interest to model the market behavior of these "successful" enterprises, we need to generate an accurate picture of future price patterns. Real world grain storage entrepreneurs consider a vast number of factors when attempting to estimate future prices. Some of these factors such as statistical price data can be immediately utilized by the computer (model), but other factors like skill, experience, inside information, or just plan gut-feelings will have to be forfeited (at least initially) by the model.1/

Several methods have been considered for generating future expected purchasing and selling prices for grains. Two methods which seem promising at present are discussed below.

1/ The methods used by the computer and human being may be entirely different, but this is no cause for alarm. After all, the objective is to accurately estimate future prices and it should make little difference how these estimates are derived, either by the human being or the computer. This writer can see possible applications of some of the concepts of intelligence adaptive systems here. Just as computer programs are in existance which improve their "skill" at playing chess through "experience," so might the KASSIM model improve its ability to predict future prices.

1) A STOCHASTIC MODEL FOR PROJECTING PRODUCER PRICES

Although in the aggregate, private market speculators' activities have an effect on market prices, no individual firm will consider its activities as having an impact on commodity prices. If prices are considered as exogenous (to each market speculator) then one possible method of projecting (predicting) future prices is to simulate them as a stochastic process with the appropriate distribution based on recent historical data.

A stochastic model for generating future expected producer prices is given by Equation (18). The individual terms that comprise the model are discussed under separate paragraphs below.

$$PPS_i(t) = PTL_i(t) + ADPTL_i(t) + ACDP_i * [DPTL_i(t-1) - ADPT_i(t-1)] + [1 - ACDP_i^{2}]^{\frac{1}{2}} * SDP_i * RN01 \quad (15)$$

where:

PPS = speculative producer price array — W/MT

PTL = expected value of price at time T represented by a price trend line (PTL) — W/MT

ADPTL = average (weighted) deviation of prices from the PTL for period (.) — W/MT

ACDP = estimate of autocorrelation between deviations of prices, from PTL with lag 1 simulation period (1/40 year) — no units

where:

DPTL = deviation of price from PTL one simulation period previous — W/MT

SDP = estimate of standard deviation of deviations of prices from the PTL — W/MT

RN01 = a random number from a normal distribution with mean zero and variance one — no units

The first term on the rhs of (15) accounts for the long-run trend of price. The second term accounts for the deviations seen about the PTL during various periods of the year. The third introduces the dependence of the amount of deviation from the PTL at time t on the amount of deviation at time t-1. The fourth term introduces the deviation from the PTL not accounted for by the deviation at t-1.

Actual statistical data is used to start the simulation run; parameters of the model of (15) are calculated based on this data. As the simulation run progresses, the state of the system changes and so do the parameters of the model in (15). New estimates of these parameters are then calculated periodically throughout the simulation run. The statistical data used to start the model is progressively replaced by actual output data from the simulation run. It is for this reason that we are not content to estimate the parameters in Equation (15) off-line from the actual simulation run. While such estimates of model parameters, based on recent real world data, may be valid for a short period into the future, it makes little sense to assume that system parameters will remain the same over the entire time horizon, say 15 years, of the simulation run.

The methods of estimating the parameters in (15) will now be discussed.

a) LONG TERM PRICE TREND (PTL)

Looking back at Figure B1(1) we see a definite trend in rice prices over the past several years. This trend may be represented by a simple regression line through the price data for, say, the last 4 years. The trend line for each commodity can be represented by the following equation.

$$PTL_i(t) = bl_{i0} + bl_{i1}t \tag{16}$$

A FORTRAN equivalent of (16) is

```
PTL(JC) = B1(1, JC) + B1(2, JC) * FLOAT(KT)                    (16F)
```

where:

PTL = the expected value of price at time t represented by the price trend line — W/MT

B1 = array of coefficients of regression for all commodities considered (JC=1,...,NC) The 1 in B1 represents the particular regression equation.

KT = time increment (DT) counter from present time — No. of DT's

Assuming we have 4 years of price data at 1/40th year intervals (160 time points), the coefficients of regression, bl_{i0} and bl_{i1} of (16) above, are given by the following expression.

$$bl_{i0} = \frac{1}{161} \sum_{I=0}^{-160} PHIST_i(I) \tag{17}$$

$$bl_{i1} = \frac{\sum_{I=0}^{-160} PHIST_i(I) * (I+80)}{\sum_{I=0}^{-160} (I+80)^2} \tag{18}$$

where:

bl_{i0} = the intercept term of the regression of prices on time — W/yr

bl_{i1} = the slope of the price trend regression line — 40W/MT-yr

PHIST = historical price data array — W/MT

The above method is inefficient and should not be used in the computer simulation program. Since the regression of (16) is along an evenly spaced time series, the matrix method of least squares estimation can be collapsed into a simple matrix multiplication. The method for determining the proper multiplier (matrix) for estimating the coefficients of (16) is described below. It should be noted that this same method can be used for other more complex linear statistical functional forms when the dependent variable can be expressed as an explicit function of time.

The general matrix form of (16F) is given by

$$E\left[P\right] = TB \tag{19}$$

where:

E = the expected value operator

P = a 160 X NC matrix with each column representing the random vector time series (for each commodity) of values of producer prices at corresponding values of $t = -160, \ldots, -1$

T = a 160 x 2 matrix of the values of the regressors (time increment points) of (16) taken for $t = -160,\ldots,-1$

i.e. $$T = \begin{bmatrix} 1 & -160 \\ 1 & -159 \\ 1 & -158 \\ \vdots & \vdots \\ 1 & -1 \end{bmatrix}.$$

The formula for least squares estimation of the coefficients for regression of the function of (16) is given below.

$$\hat{B1} = (T'\ T)^{-1}\ T'p \tag{20}$$

where:

$\hat{B1}$ = a 2 X NC matrix, with each column vector representing the value of the estimates (for each commodity) of the coefficients of (16)

T = see (19)

p = a 160 x NC matrix, representing the random sample of producer prices (for each commodity) at time points $t = -160,\ldots,-1$.

Note that the value of the 2 x 160 matrix $(T' \, T)^{-1} T'$ in (20) is fixed since the values of the regressors, t^0 and t^1, are always spaced at unit intervals of DT. This means that we can calculate the matrix (array), call it T2160, off-line and use it to estimate the coefficients of (16) at any time during the simulation run by a simple matrix multiplication. With the T2160 (2 x 160) array present, $\hat{B1}$ of (20) will result by postmultiplying this array by the matrix PHIST, whose columns (160 x 1 vectors) represent sample time series values of producer prices (for each commodity) over the sampling period. In our case, the sampling period will be 1/40 yr for 4 years or 160 time points. A FORTRAN equivalent of (20) is outlined below.

```
       .
       .
   CALL MATPRD (T2160, PHIST, 2, 160, NC, B1)
       .
       .
       .
   SUBROUTINE MATPRD (A, B, NROWA, NCARB, NCOLB, C)
   DIMENSION A(NROWA, NCARB), B(NCARB, NCOLB),
  1           C(NROWA, NCOLB)
   DØ  10  I = 1, NROWA
   DØ  10  J = 1, NCOLB
   C(I, J) = 0.                                            (20F)
   DØ  10  JA = 1, NCARB
10 C(I, J) = C(I, J) + A(I, JA) * B(JA, J)
   RETURN
   END
       .
       .
       .
```

b) DEVIATIONS FROM THE PTL (DPTL)

Much information regarding seaso... price patterns can be gained by studying the deviations of prices from the PTL of Equation (16). These deviations are determined by the following equation.

$$DPTL_i(t) = PHIST_i(t) - PTL_i(t) \qquad (21)$$

where:

DPTL = deviation from price trend line — W/MT

PHIST = historical price data array — W/MT

PTL = the expected value of price at time t represented by the price trend line — W/MT

In the interest of conserving computer storage space it is best <u>not</u> to generate PTL_i and $DFPTL_i$ as arrays with elements at each historical time point. For example, if we are working with 4 years of historical data, each array would contain 160 elements. We would then be tying up 160 x NC (number of commodities) stora... locations. An alternative method is to generate PTL and DFPTL on-line for the particular commodity/time point in question at the time. This will be done in what follows.

c) AVERAGE DEVIATIONS FROM THE PRICE TREND LINE (ADPTL)

We now have at our disposal (through FORTRAN calculations) the deviations from the price trend line over the past, say, 4 years. Next we need to compute an average deviation from the trend line for each simulation time period during a year. A weighted average, giving more influence to recent data seems logical here. Although at the present time these weights are arbitrarily assigned, the possibility of some weighting combinations giving better results than others should be investigated at a later date. If this can be shown as true, then a good possibility exists here to apply intelligence adaptive principals whereby the computer program may improve its speculative "skills" with "experience"

Intitially we will assume a declining geometric sequence of weights, namely

$$W_i = (1 - \lambda)\lambda^i \qquad 0 < \lambda < 1 \tag{22}$$

where:

W_i = the weight given to the ith most recent year of historical data

λ = a weighting factor — when is close to zero more recent data is weighted heavily

If i approaches infinity the sum of the weights in (22) converge to 1. However, since our historical data is finite, these weights must be normalized to sum to unity. In the case where i = 4, we have

$$W_i = \frac{(1-\lambda)\lambda^{i-1}}{1-\lambda^4} \qquad \begin{array}{l} 0 < \lambda < 1 \\ i = 1, \ldots\ldots, 4 \end{array} \tag{23}$$

A FORTRAN equivalant to (23) is given below.

```
W1 = (1 - WT)/(1 - WT**4)                                    (23F)
W2 = W1 * WT
W3 = W2 * WT
W4 = W3 * WT
```

The reader may verify that these 4 weights sum to unity. We will arbitrarily choose $\lambda = \frac{1}{2}$ for model development purposes. Using (23F) we see that the weights assigned to past years' data are then 8/15, 4/15, 2/15 and 1/15 respectively. The (weighted) average deviations of commodity prices from the trend line for the 40 simulation time periods throughout a year are generated by the following FØRTRAN statements:

```
  DØ 1 JC = 1, NC                                            (24F)
  DØ 1 I = 1, 40
  DPTL4 = PHIST(I, JC) -(B1(1, JC) + B1(2, JC) * FLOAT(I-161))
  DPTL3 = PHIST(1+40, JC) - (B1(1, JC) + B1(2, JC) * FLOAT(I-121))
  DPTL2 = PHIST(I+80, JC) -(B1(1, JC) + B1(2, JC) * FLOAT(I-81))
  DPTL1 = PHIST(I=120, JC) - (B1(1, JC) + B1(2, JC) * FLOAT(I-41))
1 ADPTL(I, JC) = W1 * DFTL1 + W2 * DFTL2 + W3 * DFTL3 + W4 * DFTL4
```

d) AUTOCORRELATION AND STANDARD DEVIATION OF PRICE DEVIATION (ACDP AND SDP)

It is obvious that price data is strongly autocorrelated with its previous values. Before an accurate model can be developed to estimate futur_ ,rices, the autocorrelation of prices during the different time periods of the year will have to be determined. The accurate determination of these coefficients is the subject of future study. For the present, however, let us assume that the autocorrelation is constant throughout the year and thereby estimated via the following statistic.

$$ACDP_i = \sum_{t=2}^{NS} (DPTL_i(t) - ADPTL_i(t)) * (DPTL_i(t-1) - ADPTL_i(t-1))/ \quad (25)$$
$$SDP_i^2/(NS-2)$$

where:

ACDP = estimate of autocorrelation between deviations of prices from PTL with lag of 1 DT. — no units

DPTL = deviation of prices from the PTL (calculated on-line) — W/MT

NS = number of sample time points

ADPTL = weighted average deviation of prices from PTL for the period of the year corresponding to (.) — W/MT

SDP = standard deviation of the deviations of prices from the PTL — W/MT

The expression for the standard deviation SDP in Equation (25) in given below.

$$SDP_i = \left[\sum_{t=1}^{NS} (DPTL_i(t) - ADPTL_i(t))^2/(NS - 1) \right]^{\frac{1}{2}} \quad (26)$$

There is a slight notational difficulty in Equations (25) and (26). Recall that ADPTL has been calculated for only 40 periods during the year, while the summations in (25) and (26) are taken over NS sample points, possibly corresponding to several years of data. The index of ADPTL is then not really t, but the period of the year corresponding to t or t-1 (whichever the case may be). A FØRTRAN equivalent of Equations (25-26) is given below; note how the above difficulty is circumvented.

(25F-26F)

```
  DØ 1 JC = 1, NC
  DPTL = PHIST(1, JC) - (B1(1, JC) + B1(2, JC)) * (-160.)
  SUMA = 0
  SUMB = (DPTL - ADPTL (1, JC)) ** 2
  J = 1
  DØ 2 I = 2, NS
  J = J + 1
  IF (J. GT. IDT) J = 2
  DPTL1 = DPTL
  DPTL = PHIST(I, JC) - (B1(1, JC) + B1(2, JC) * FLOAT(I-161))
  SUMA = SUMA + (DPTL - ADPTL(JC, J))* (DPTL1 - ADPTL(JC, J-1))
2 SUMB = SUMB + (DPTL - ADPTL (JC, J))**2
  SSDP(JC) = SUMB/FLØAT (NS-1)
1 ACDP(JC) = SUMA/SSDP(JC)/FLØAT(NS-2)
```

This completes the present discussion of the proposed stochastic model for predicting producer prices. We now describe alterative methods by which this predicted price pattern may be smoothed.

2) SMOOTHING THE PROJECTED PRICE PROFILES

The projected producer prices, generated through the stochastic model of Paragraph 1) above, will exhibit a fair amount of random variation. Since we are interested more in the general characteristics and levels of projected prices, we can simplify some of the information available by smoothing the speculative price arrays (PPS).

a) POLYNOMIAL FUNCTIONAL FORM FOR SMOOTHING PROJECTED PRICE PROFILES

A 4th order polynomial can be selected for fitting the PSS array (sample) for the following reasons: (1) It is a linear statistical form and standard multiple regression techniques can be applied. (2) The general shape of a 4th order polynomial, with 2 inflection points, should lend itself fairly well to giving a fit through the time points of PSS without destroying the general cyclical nature of the pattern. (3) It may be described to solve the functional form chosen for critical points as well as inflection points (first and second derivatives). Numerical methods available for the solution of higher order polynomials can be applied. Of course the above hypothesis will have to be tested to verify that the chosen functional form does indeed give an adequate fit.

The functional form chosen for fitting a curve through the random sample PPS (time series) array is given below.

$$YP(t) = b2_{i0} + b2_{i1}t + b2_{i2}t^2 + b2_{i3}t^3 + b2_{i4}t^4 + U_i \qquad (27)$$

A FØRTRAN equvalent of (27) is

```
YP(JC) = B2(1, JC) + B2(2, JC) * FLØAT (KT)                    (27F)
```

```
1      + B2(3, JC)* FLØAT (KT**2)
2      + B2(4, JC)* FLØAT (KT**3)
3      + B2(5, JC)* FLØAT (KT**4)
```

where:

YP = the expected value of price E(PPS) at k time increments (DT's) into the future ($k = 1,\ldots,40$)

B2 = array of coefficients of regression for all commodities considered ($JC = 1,\ldots,NC$)

KT = time increment (DT) counter from present time — No. of DT's

Again, following the procedure of Section B.1.a.1)a), the matrix form of (16F) is given by

$$E\left[YP\right] = TB \qquad (28)$$

where:

E = the expected value operator

YP = a 40 x NC matrix with each column vector representing the random vector time series (for each commodity) of values of producer prices at corresponding values of $t = -40,\ldots,-1$

T = a 40 x 5 matrix of the values of the regressors (time increment points) of Equation (27), taken for $t = -40,\ldots,-1$

i.e. $$T = \begin{bmatrix} -1 & -1 & 1 & -1 & 1 \\ 1 & -2 & 4 & -8 & 16 \\ 1 & -3 & 9 & -27 & 81 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 1 & -40 & 1600 & -6400 & 2{,}560{,}000 \end{bmatrix}$$

The formula for least squares estimates of the coefficients for regression of the function of (27) is given by

$$\hat{B2} = (T' \; T)^{-1} T' \left[yp \right] \tag{29}$$

where:

$\hat{B2}$ = a 5 x NC matrix, with each column vector representing the value of the estimates (for each commodity) of the coefficients of (27)

T = see (28)

$[yp]$ = a 40 x NC matrix, representing the random sample of producer prices, i.e., this is the PPS array.

b) FOURIER SERIES MODEL FOR SMOOTHING PROJECTED PRICE PROFILES

A general Fourier series with a time-trend term will be used for smoothing PPS. The functional form of this regression equation is shown below.

$$YP_i(t) = b3_{i1} + b3_{i2}t + \sum_{n=1}^{N} (b3_{i,2n+1} \sin nw_0t + b3_{i,2n+2} \cos nw_0t) \tag{30}$$

where:

YP = the expected (smoothed) value of the projected producer price array (PPS) represented by the regression — W/MT

b3 = coefficients of the regression terms

t = time, based on current simulation time — years

N = number dictating the high frequency used (initially we will use N = 3)

w_0 = fundamental frequency ($2\pi/T$) of the Fourier series — radians/yr (T = the period of the Fourier series — yr)

A FORTRAN equivalent of (30) is given below.

```
PI = 3.14159265
 .
 .
 .
YPPS(JC) = B2(1, JC) + B2(2, JC)*TC                        (30F)
                     + B2(3, JC)* SIN(2.*PI*TC)
                     + B2(4, JC)* COS(2.*PI*TC)
                     + B2(5, JC)* SIN(4.*PI*TC)
                     + B2(6, JC)* COS(4.*PI*TC)
                     + B2(7, JC)* SIN(6 *PI*TC)
                     + B2(8, JC)* COS(6 *PI*TC)
```

In matrix notation (30F) becomes,

$$E\,\boxed{PPS} = TB \tag{31}$$

where:

E = the expected value operator

PPS = a 40 x NC matrix with each column representing the random vector time-series (for each commodity) of values of predicted producer prices at corresponding values of t = .025, .05,...1.

B = a 8 x NC matrix of the r.v. coefficients of (27)

T = a 40 x 8 matrix of values of the regressors (functions of time) of (30) taken for t = .025, .05, ...1.

$$\text{i.e. } T = \begin{bmatrix} 1 & .025 & \sin 2\pi(.025) & \cos 2\pi(.025) \ldots & \sin 6\pi(.025) & \cos 6\pi(.025) \\ 1 & .050 & \sin 2\pi(.05) & \cos 2\pi(.025) \ldots & \sin 6\pi(.05) & \cos 6\pi(.05) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1. & 1. & \sin 2\pi & \cos 2\pi & \sin 6\pi & \cos 6\pi \end{bmatrix}$$

Since (30) the values of the regressors in the matrix T are always the same, we can again compute the proper value of the multiplier matrix $(T' \; T)^{-1}T'$ of L.S.E. off-line. Then this matrix can be used to smooth the PPS array at any time during the simulation run by performing a single matrix multiplication. Recall that

$$\hat{B2} = (T' \; T)^{-1}T' \left[PPS \right] \tag{32}$$

where:

$\hat{B2}$ = an 8 x NC matrix, with each column vector representing the values of the estimates (for each commodity) of the coefficients of (30)

T = see (30)

$(T' \; T)^{-1}T'$ = an 8 x NC matrix, calculated off line

$PP\dot{S}$ = a 40 x $N\dot{C}$ matrix — the speculative producer price array

3) PROJECTING CONSUMER PRICES

Assuming that current selling price is equal to the current purchasing price plus some fixed marketing margin, then

$$PSS_i(t) = (1 + MM_i) * PPS_i(t) \tag{33}$$

where:

PSS = speculative selling price — W/MT

PPS = speculative purchasing price — W/MT

MM = marketing margin — no units

Further research is needed to improve the relationship expressed in (30) above. For example, it has been shown that the marketing margin is changing over time for various commodities. Marketing margin also depends on the direction of change in price. For now, however, we will continue to assume a constant marketing margin for all commodities.

b. PROFITABILITY AND PROFIT PROJECTIONS

1) SPECULATIVE PROFITABILITY ON CURRENT PURCHASES (SP_i)

The behavior of market speculators is influenced in a large way by the speculated profitability of taking advantage of seasonal and longer-run price changes. This speculative profitability for commodity i is given by the following equation.

$$SP_i(t,th) = PSS\,(t\text{-}Th) - P_i(t) - [\,INT(t) * P_i(t) + A1_i\,]^{*} Th - A3_i - A4_i \qquad (34)$$

where:

SP = speculative profitability — W/MT

PSS = speculative selling price — W/MT

P = current purchasing price — W/MT

INT = interest rate — %/yr

A1 = storage and handling costs — W/MT-yr

Th = holding time of purchases — yrs

A3 = selling cost — W/MT

A4 = acquisition cost — W/MT

Equation (34) can be used to investigate the speculative profitability of various holding times on current purchases. Given the speculative selling prices for a period of one or more years into the future, successive the maximum value of speculative profit and the corresponding holding time.

A slight modification to (34) enables us to investigate the maximum value of speculative profitability on future purchases.

2) SPECULATIVE PROFITABILITY PROFILE (SPP_i)

Given the speculative producer prices of (15) — smoothed in (27) or (30) — and the speculative consumer prices of (33), the speculative profitability profile is defined as an array of maximum attainable profitabilities for all time periods (in our case 40) during the upcoming year. More specifically, for any time period during the next year, the corresponding value of the profitability profile is the maximum profitability which can be realized on food grains purchased at that time (SPP) and hold for a time necessary to maximize profitability (OTH).

Each member of the SPP array is calculated as the maximum speculative profitability attainable over all holding times from zero to one year.[1/]

[1/] The possibility of feasible holding times of more than one year will be left open. As indicated in Figure B1(1), the long-term price trend rises (neglecting seasonal fluctuations) of some commodities may warrant such investigation.

$$SPP_i(t) = \underset{\forall T_h}{MAX} \left\{ PSS(t+Th) - PPS_i(t) - \left[INT * PPS_i(t) + A1_i \right] * T_h - A3_i - A4_i \right\} \quad (35)$$

for all t (increments of DT) over the next year.

where:

SPP = speculative profitability profile array –– W/MT

MAX = the maximization function (direct approach)

$\forall$ = symbol meaning "for all"

PSS = speculative selling price –– W/MT

PPS = speculative purchasing price –– W/MT

INT = interest rate –– %/yr

A1 = storage and handling costs –– W/MT-yr

Th = holding time of purchases –– yrs

A3 = selling cost –– W/MT

A4 = acquisition cost –– W/MT

A FORTRAN equivalent which will accomplish the above SPP array is outlined below.

```
DØ  15  JC = 1, NC        (commodity index)
SPMAX = -9.0E20
DØ 15 K = 1, 40           (future time period index)
DØ 15 LTH = 1, 60         (length of time held index)
SPP(JC, K) = AMAX1 (SPMAX, PSS(JC, K + LTH) - PPS(JC, K)                  (35F)
1             - (INT * PPS(JC, K) + A1(JC)) * FLØAT (LTH)
2             - A4(JC) - A3 (JC))
```

```
   IF (SPP(JC,K).GT.SPMAX) IØTH(JC,K) = LTH
   IF (SPP(JC,K).GT.SPMAX) SPMAX = SPP(JC,K)
   IF (IØTH(JC, K).GT.41)   PRINT 16
15 CØNTINUE
16 FØRMAT (1H, 27H HØLDING TIME GT 1 YR FEASIBLE)
```

At this point we have an array SPP, representing the speculative profitability profile on purchases over the next year, and the array OTH, containing the speculative optimal holding time associated with each element of SPP. It is through these 2 arrays, given no prior information on "seasonal" demand patterns other than an expected annual average demand, that we will attempt to simulate the marketing behavior of rational market speculators. If we <u>are</u> given prior information on seasonal demand patterns, i.e., if we assume the PM speculators have a-go-at seasonal demand profile projections as well, then further consideration must be given to speculative profit projections.

3) SPECULATIVE PROFIT PROFILE (SFF_i)

If speculators are attempting to take advantage of any seasonal variation in market demands, it is necessary for them to consider profits (W/yr) rather than profitabilities (W/MT). With a constant (annual average) demand facing speculators, profits and profitabilities are linearly related. However, if demand is changing over time, along with profitability, then profits and profitabilities are no longer linearly related and maximum profits will not necessarily come at the same time as maximum profitabilities. Since speculators are maximizing profits and not profitabilities, the speculative profit profile must be used as a bases for simulating behavior.

Speculative profit is simply speculative profitability times speculative demand.

$$SF_i(t) = SP_i(t, t_h) * SUD_i(t, t_h) \tag{36}$$

where:

SF = speculative profit — W/yr

SP = speculative profitability — W/MT

SUD = speculative urban demand — MT/yr

Just as with the speculative profitability, we can project a speculatative profit profile.

$$SFF_i(t) = \underset{\forall t_h}{MAX} \left[\left\{ \left[PSS(t+t_h) - PPS_i(t) - \left[INT * PPS_i(t) + A1_i \right] * t_h - A3_i - A4_i \right\} * SUD_i(t, t_h) \right] \tag{37}$$

for all t (increments of DT) over the next year.

where:

SFF = speculative profit profile array — W/yr

SUD = speculated urban demand profile array — MT/yr

c. URBAN DEMAND PROJECTIONS

In order to logically calculate the private marketing demand necessary to adjust present inventory levels, the PM subsector model must have some access to expected future demand rates of existing stockpiles. At any particular point in time, PM demand will be aimed at adjusting stockpiles to a level which will enable the realization of the speculative optimal holding times on future purchases. This concept will be discussed in detail in a later section of this paper. In this section, means of projecting future urban demand will be discussed.

1) INITIAL APPROACH - USE OF BEHAVIORAL RESPONSE FUNCTION USED IN SIMULATION

The same seasonal urban demand response functions to be initially used to run the urban demand subsector component in a fine-time mode can also be used for making urban demand profile projections. A discussion of the details of this particular response function will be given in a later section of this paper. The reader may question the "fairness" of using the <u>exact</u> same functional response relationships for projections as are used to describe <u>actual</u> response. This trick awaits critisism; however, one thing seems evident at this time. By using such a tactic to project future urban demands, the observed performance of the demand predictor is fully determined by the integrity of the prediction mechanisms used for the explanatory variable (mainly prices)... Programming details will be described in a later sector.

(2) ALTERNATIVE APPROACH

2. DECISION MECHANISM

It will become evident in this section (if it hasn't already) that a very versatile and efficient information storage and retrieval system will have to be available in the simulation program. This system is discussed in section B5. The reader is welcome to turn to that section at any time he wishes.

a. PM INVENTORY CAPACITY ALLOCATION

1) THE PROBLEM

It should be obvious that in order to take advantage of the commodity profit functions, PM inventory levels must fluctuate throughout the year. Inventory should be at a low level during period of high profitability on current purchases so that speculators are not constrained by available storage space. On the other hand, inventory should be sufficiently high to carry the PM sector through periods of low profitability on current purchases. When multiple commodities which compete for the same storage space are taken into consideration, the problem facing the PM speculator begins to come into view. The profit functions for most commodities are very dissimilar both in amplitude and phase throughout the year, due to different growing seasons, different costs, demands, prices, etc. It is not hard to visualize the situation in which the PM speculator would like to let an existing commodity stock level dimmish in order to make 'room' for purchases at a later high profitability period -- but at the same time being faced with a high current profitability on a competing commodity. He is therefore faced with the dilemma of trying to allow one inventory level to deplete while at the same time trying to build another inventory level. Those who do best in the PM speculative game will be those who can time and control specific commodity purchases in a way which will take full advantage of existing inventory capacity and maximize overall profits from grain storage.

In the short-run, PM speculators must allocate the current inventory capacity among the various commodities in a manner which will maximize profits. In the long run, PM speculators must decide if more overall capacity is feasible and, if so, obtain and then allocate this additional storage capacity in the most profitable manner.

2) A SOLUTION

It is not adequate to assume that total inventory capacity can be allocated among commodities based on current profitabilities and then fixed at this allocation throughout the crop year. It is equally or even more inadequate to allocate storage space to the competing commodities in a dynamic fashion based on current profitabilities. If the seasons of 2 crops are very dissimilar, it is possible that the same two crops may utilize the same storage space. As one inventory level is built up, the other can diminish. For example, barley and rice may share the same warehouse, although their respective levels will fluctuate. The current profitability of commodities does not indicate how inventory should be allocated, even in a dynamic sense. Current profits are not necessarily made on current purchases. When there are inventories involved, current profit is based on past purchases. A high current commodity profit may indicate that there should have been a large allocation given to the commodity at the time it was purchased, but it does not indicate that a large allocation should be given to the commodity at the current time. In fact, high profits would tend to go with high prices. For high profits, purchases should be kept at a minimum during these periods.

The problem of devising a method for allocating inventory capacities through time, so as to maximize total profits from grain storage, is no small task. The method which has been chosen for the initial versions of this model may well be improved at a later date; however, it is very appealing in many ways at this time. This method of allocating storage capacities among competing commodities is not to allocate storage at all! Instead of putting a ceiling on the inventory level of each commodity, they all bid for the same empty space until it is filled.

Two possibilities exist. Either inventory capacity is an active constraint or it is not. If there _is not_ a shortage of available storage space, there is no need to allocate this space among commodities. Speculative purchases will be made in such a way as to adjust inventory levels (upward) in attempting to achieve the optimal holding times on current purchases which were calculated during the speculative phase of the model. If there _is_ an available storage space constraint, priority will be given to the most profitable commodities. Purchases will then be foregone on the less profitable commodities.

b. PM INVENTORY CAPACITY ADJUSTMENT (LONG-RUN)

It is not correct to assume that the most profitable inventory capacity is the maximum expected total inventory level. As inventory capacity drops below this threshold, there will be periods during the year (or speculation cycle) when inventory becomes completely filled and purchases (and the profits on those purchases) must be foregone. One must also remember, however, that a lower inventory capacity level means less capital costs. By lowering inventory capacity level we may have to forfeit profits on purchases (of least profitable commodities) during a few periods of the year, but at the same time we are enjoying inventory capacity overhead cost savings throughout the entire year. There is a point at which the profits foregone due to inventory capacity constraints are equal to the savings in overhead costs. This is the "optimal inventory capacity level."

The level of private marketing inventory capacity is determined by the profitability of either increasing or decreasing the amount of available storage capacity. If less storage is more profitable because of the expense of carrying excess capacity, we will see a gradual decrease in PM storage capacity. If additional storage space is seen to be more profitable, even after adequately considering the construction costs of this storage, then we will see an increase in the amount of PM storage capacity.

The optimum level of PM storage depends on a multitude of factors and will continue to change throughout time. It seems safe to assume that although actual PM storage capacity will move toward this optimum level, it may never arrive; and if it did arrive at any particular point in time, changing conditions would soon change this optimum level.

First attempts at simulating the above phenomena will be as described below. Several of the performance criterion described in section B4 (and perhaps others, if necessary) will be carried by the simulation model at 3 different levels of PM inventory level: (1) the actual level, (2) a slightly lower level (perhaps 10 percent), and (3) a slightly higher level. The variable carried at these 3 levels will be those which are dependent on PM inventory level and will in-term reflect their effects on actual PM profits realized. If, at a particular point in time, the 3 levels of criterion indicate that profits are increased by a higher level of capacity, after accounting for increased costs due to construction and overhead, then there will be an increase in PM storage capacity. The same thing can be expected in the opposite direction if there is excess storage capacity. Finally, we can expect to see no change in the amount of storage capacity if both higher and lower levels point toward lower profits.

c. PM INVENTORY (STOCKPILE) ADJUSTMENT

1) COMMENT ON DYNAMIC PROGRAMMING

There are several means of generating PM demand and marketing patterns which will reflect an 'attempt' on the part of PM speculators to maximize their profits. Perhaps the most elegant method to use would be a dynamic programming approach. In this initial phase of model development, however, we shall avoid getting too involved with sophisticated optimization techniques. Perhaps the shortcomings of the alternative methods discussed in this paper will serve to reflect some of the imperfectness of the human behavior patterns being simulated. Dynamic programming is a very powerful computational technique which should not be dismissed from later applications in the KASSIM model. When developing optimal policy strategies for the government food-grain management program, dynamic programming, in conjunction with the simulation model, can provide valuable answers to very difficult questions.

2) PM SPECULATIVE DEMAND AND MARKETINGS

The methods described in this section for generating speculative PM demands and marketings make use of the information storage and retrieval (ISR) mechanism. The details of how information manipulations are actually carried out by the simulation program are described in Section B.5.c. of this report. The reader should keep in mind that several variations and refinements of the procedure described in this section are possible, using the same ISR mechanism.

In the following discussion, a time-cell (T-C) can be defined as an identifiable and accessible set of numbers, containing information relevant to a specific time period of the simulation model. T-C information can be past (historical or memory), present, or future (speculation). It can be accessed, manipulated, and "forgotten" when no longer useful. Once T-C information has been "forgotten," the same computer storage space can be utilized by a new T-C and its information.

Given T-C information about inventory stock levels, current inventory capacity, and appropriate data generated during the speculation phase, it is possible to generate PM demand and marketing patterns which reflect logical profit maximizing maneuvers on the part of market speculators.

The illustration below will help to clarify some of the general ideas behind this method of generating PM demands and marketings.

$$\begin{array}{ccccccccc}
 & NTIME_1 & NTIME_2 & NTIME_3 & \cdots & NTIME_m & \cdots & NTIME_{40} \\
(1) & a_{11} & a_{12} & a_{13} & \cdots & a_{1m} & \cdots & a_{140} \\
(2) & a_{21} & a_{22} & a_{23} & \cdots & a_{2m} & \cdots & a_{240} \\
(3) & a_{31} & a_{32} & a_{33} & \cdots & a_{3m} & \cdots & a_{340} \\
\vdots & \vdots & \vdots & \vdots & & \vdots & & \vdots
\end{array}$$

The columns of the matrix represent consecutive T-C's, beginning at the time projections are made. Speculative projections are made over a time horizon of 1 year (40 time points) and updated every $\frac{1}{4}$ year (10 time points) with "most recently" aquired data. Each row of the matrix above is assigned to contain a certain attribut of time point information. For example, NTIME contains the identifier of the particular time point. Row (1) might contain PFF, the array representing the speculative profit profile on "current" purchases, and row (2) might contain the corresponding optimal holding time for purchases at each time point. Row (3) might contain the projected urban demand at the end of each optimal holding time. The reader should note that for each time point during a simulation run there is assigned one and only one time-cell. A T-C is not assigned until there is a need to store information related to the particular time point. Since information about a particular (future) time point is generated during the projection phase, this is usually when T-C's are assigned. Projection information, however, is not the only type of information to be contained in a T-C.

With the ISR mechanism, we have immediate access to of any T-C through any attribute. For example, we can access the T-C representing the time point in the projection corresponding to the maximum speculative profit. This would be accomplished by calling for the removal of the T-C containing the maximum value of PFF in row (1) of the matrix illustrated above. A simple procedure for generating PM demands and marketings follows

(1) Access T-C containing maximum value of PFF as described above.

(2) Determine the projected total urban demand for the coming year.

(3) Determine the amount of deficit inventory at the time of projection by subtracting current inventory level from the value found in (2).

(4) Generate an impulse function of size one-fourth the value in (3).

(5) Place the impulse generated in (4) into a distributed delay with mean centered about the time point in (1).

(6) Generate a second impulse of size one-fourth the value in (2).

(7) Place the impulse generated in (6) into a distributed delay with mean centered about the time point represented by the sum of the time point in (1) plus its optimal holding time.

(8) Run the simulation model for $\frac{1}{4}$ year. The output from the delay in (5) will represent private demand to adjust inventory (PDAI). The output from the delay in (7) will represent private marketings.

The above discussion has been a very brief introduction as to how PM demand and marketing patterns might be generated. It is far from being the final word.

3) USE OF THE DELDT DELAY ROUTINE IN GENERATING PM DEMANDS AND MARKETINGS

If distributed delay functions are used to generate PM marketing patterns as introduced in section 2) above, the following discussion may be of assistance to programmers.

At any particular time point at which a projection is performed (i.e., every ½ year), the PM speculator (the model) can determine the 'gap' between actual inventory level and the estimated level of inventory which would be required to supply urban consumers over the next year.

$$PIGAP_i(t) = TSUD_i(t) - PINV_i(t) \tag{38}$$

where:

PIGAP = PM inventory gap — MT

TSUD = to speculative urban demand — MT

PINV = actual PM inventory level — MT

An impulse representing this gap in required inventory is generated as follows.

$$PDIR_i(t) = PIGAP_i(t)/DT \tag{39}$$

where:

PDIR = PM demand 'impulse' to adjust inventory — MT/yr

PIGAP = PM inventory gap — MT

DT = lenth of simulation cycle (1/40 year) — yr

The DELDT delay subroutine will enable us to "spread" this unrealistic demand 'impulse' rate over a longer time period. The order of the delay will reflect the acquisition efficiency of the PM subsector — higher orders, reflecting higher acquisition efficiency. The DEL parameter (mean delay time) of the delay (TTD below) is the instrument by which the demand to adjust inventory is centered on the proper time point.

The FORTRAN sequence below indicates this method for calculating PM demand to adjust inventory.

```
PDIR(JC) = PIGAP(JC)/DT                                                  (39F)
CALL DELDT (PDIR(JC), PDAI(JC), RINFG1, TTD(JC), IDTFG1(JC),
           DT, KFG1)
```

where:

PDIR = PM desired 'impulse' to adjust inventory for commodity JC (import to delay) — MT/yr

PDAI = PM demand to adjust inventory for commodity JC (output of delay) — MT/yr

RINFG1 = array of intermediate rates used by the DELDT subroutine — MT/yr

TTD = the simulation time point at which speculative profits on "current" purchases an at a maximum — yrs

IDTFG1 = the number of subdivisions of DT effective in this particular call to DELDT.

IDTFG1(JC) = 1.+2.*FLOAT(KFG1(JC))*DT/TTD(JC) (40F)
(see discussion below)

where:

DT = simulation time cycle (1/40 yr) — yr

KFG1 = order of the DELDT delay — representing the acquisition efficiency of PM — no units

Note that the length of the delay (TTD) in (39F) is variable. For each profit profile projection a new value of TTD is determined. There is nothing to keep TTD from occuring very near to the projection phase time point. One can certainly see the need for the DELDT instead of the ordinary DELAY delay subroutine in this case. (Reference pp 6-47 to 6-51 of Llewellyn). In the worst case (when $TTD_i - t_0 = .025$) the effective DT of DELDT subroutine should be 1+2k times smaller than the DT of the model (where k is the order of the delay) to insure stability. The argument ILTFG1(JC) is, therefore, calculated after each speculation phase of the model. Similar arguments to the above apply to the generation of PM marketings.

4. SELF-ADAPTIVE MECHANISM

Reasons for incorporating a self-adaptive (or learning) mechanism into the PM behavioral model have already been discussed in several previous sections of this paper. The updating of the parameters used in the Stochastic Model for Predicting Prices (Section B.2.a.1)) is a part of this self-adaptive mechanism. In this section we will discuss some further aspects of this portion of the model.

a. PERFORMANCE CRITERIA

Up to this point, a large factor in determining the behavioral patterns of the PM subsector has been the speculative profit on current and future purchases. An excellent (and most logical) criteria to use for evaluation of this predicting procedure is the actual profit eventually realized on these purchases! Much of this information is not immediately available, and it is therefore necessary to "hold" the original predictions until such time that a comparison between actual and predicted values can be made. For example, when a PM entrepreneur purchases a certain amount of grain at a specific point in time, the profitability or profits actually realized on those particular purchases will not be available until the grain is sold and the actual revenue and costs associated with the original purchases are determined. It is this type of stimulus, the "actual" performance criteria (oftentimes lagged), which will concern us most in this section, By utilizing this information the PM system can internally adjust (1) inventory capacities, (2) inventory levels, (3) purchasing patterns, and (4) predicting mechanisms to improve its own performance and increase PM profits — a phenomenon not unlike real world behavior, which is our objective here.

It is widely agreed that if one disappearance pattern for grains from storage had to be described, it would be a first-in-first-out (FIFO) pattern. Old grains lose their taste and preference rapidly and all dealers attempt to rid these inventorie of the oldest commodities first.

If we can hold (in a time-cell) various PM variables for each time point (DT) during a simulation year we will have access to some very valuable "actual" performance criterion for the PM subsector. These criterion can then be fed back into the model to improve performance. Some of the variables for which T-C information can be of use are listed below:

1. Speculative Price Projections, PSS — W/MT

   Price projections are the bases for all other speculation. By holding T-C information on projected prices and then comparing it with actual realized prices, we have a means of evaluating and correcting the price projection mechanism.

2. Speculative Profitablities on Current Purchases, SPP_i — W/MT

   A comparison between actual profitabilities and this

T-C information will be a direct measure of the performance of the projection mechanism.

3. Speculative Profits on Current Purchases, SPF_i -- W/yr

Speculative profits are based on both speculative profitabilities and speculative urban demand. A comparison between actual profits realized and this T-C information will be a measure of the performance of the combination of these projection mechanisms.

4. Speculative Urban Demand Rate, SUD_i -- MT/yr

This T-C information can be used to evaluate and correct the urban demand projection mechanism.

T-C information on the rates at which inventories can be expected to move gives us a means of estimating the holding times on current purchases. Given current inventory level, and the expected disappearance rates from successive time-cells, it is possible to estimate the holding time on current inventory. If the expected holding time on current inventory is longer than the optimal holding time calculated for purchases during this time period, inventory level is indicated to be too high and it is best to forego any purchases during this time period. If, on the other hand, expected holding time on current inventory is shorter than the optimal (speculative) holding time calculated for purchases during this time period, then current inventory is indicated to be too small to provide the appropriate holding time.

Again, given the expected disappearance rates, it is possible to calculate the purchasing rate for that period which will provide the appropriate expected holding time on those purchases. Of course there are many constraint action on the system at this point (e.g. acquisition efficiency, supply, available inventory capacity, available funds, etc.).

5. Speculative Optimal Holding Times, OTH_i -- yrs

This information can be used to generate (varying degrees of) "profit maximizing" PM demand and marketing behavioral patterns.

6. Commodity Specific Inventory Levels, $PINV_i$ -- MT

If we have this T-C information for, say, the past year, we have continuous access to the amount of inventory carryover generated by a particular PM strategy.

7. Total Inventory Level, TPINV -- MT

T-C information on the utilization of current inventory capacity will give us information which can be used in long-run inventory capacity adjustments.

8. Level of PM Purchases, $PPUR_i$ -- MT/yr

We must have a record of actual T-C purchases to evaluate actual profitabilities and profits realized on purchases. This list is not meant to include all time-cell specific variables which may be of interest. As development continues, some variables may be added or deleted from the above list.

b. CORRECTION FACTORS

Note that speculation is made only on 2 variables — future price and future demand. Since a record has been kept of the speculative profile of each of these variables, it is a simple matter to calculate a correction factor for the original prediction mechanisms, once the actual price or actual demand for a particular T-C has been observed. These correction factors are then used in the new prediction phase.

$$PCF_i(KT) = (CPU_i(KT) - PSS_i(KT))/PSS_i(KT) \tag{41}$$

$$QCF_i(KT) = (Q_i(KT) - QS_i(KT))/QS_i(KT) \tag{42}$$

where:

PCF = correction factor for price predicting model — %

KT = yearly time-cell index (KT=1,...., 40)

CPU = actual consumer price — W/MT

PSS = speculative selling price — W/MT

UDCF = correction factor for demand predicting model — %

UD = actual nonfarm demand — MT/yr

SUD = speculative demand -- MT/yr

The old prediction mechanisms are then modified as indicated below. Note the predictions from the old mechanisms appear on the rhs of the replacement symbol (=).

5. INFORMATION STORAGE AND RETRIEVAL MECHANISM

a. PRICE DATA ADJUSTMENTS

Since the model is presently designed to operate with a simulation time cycle period of 1/40 year, it will be highly preferable to have price data based on at least 40 independent observations per year. Weekly data would be more than sufficient and could easily be transformed into 40 independent observations per year through the use of the TABLEXE function.

A word will now be said about how data can be easily transformed into 40 equally spaced time points per year. Although monthly data are too coarse for the purpose we have in mind here, it may be necessary to start the model with such data in the beginning since additional research will have to be done in uncovering the finer time scale data.

Suppose 4 years of monthly data are to be transformed into 1/40 year data. The data can be loaded by the following DATA statements.

DATA ((VALP(1, M), M=1,48) = d_{11}, d_{12},.................., d_{148}) (45F)

DATA ((VALP(2,M), M=1,48) = d_{21}, d_{22},.................., d_{248})

•
•
•
etc.

where:

VALP = an array to hold monthly prices for the NC (number of commodities) — W/MT

d = price data

This monthly data can now be transformed into 1/40 year data by utilizing the TABLEXE function as follows:

```
      DØ  2  JC = 1, NC                                         (46F)
      DØ  2   M = 1, 48
  1   VALPS(M) = VALP(JC, M)
      DØ  2   I = 1, 160
  2   PHIST(JC, I) = TABLEXE(VALPS, 1, 1, 47, .3* FLØAT(I))
```

Four years of <u>weekly</u> data can be loaded and transformed into 1/40 year data by the following statements.

```
      DATA ((VALP(1, MW), MW=1,208) = d11, d12,................d1208)   (47F)
              .
              .
              .
      DØ  2  JC = 1, NC
      DØ  1  MW = 1, 208
  1    VALPS(M W) = VALP(JC, MW)
      DØ  2  I = 1, 160
  2   PHIST(JC, I) = TABLEXE(VALPS, 1, 1, 207, 1.3*, FLØAT(I))
```

b. UPDATING HISTORICAL DATA USING CYCLIC BOXCAR ROUTINES

In this section we will discuss a method in which historical data can be progressively replaced by actual corresponding output data from the simulation run.

In some cases it is not necessary (and a waste of machine efficiency) to 'carry along' newly generated data every simulation cycle. Instead, the model may operate for, say, $\frac{1}{4}$ year (10 simulation cycles) before updating certain historical data arrays. The cyclic boxcar subroutine given below enables us to 'update' historical data arrays at specified intervals throughout the simulation run.

(Ref. Llewllyn, Chapter 7)

```
SUBROUTINE CBOX2 (CYCLE, CYCLEU, LT, NCY, NK, CTP)                (48F)
DIMENSION CYCLE(1), CYCLEU(1)
NK = NK + 1
CYCLEU(NK) = CTP
IF (NCY. GT. NK) GØ TØ 1
K = LT - NCY
DO 2 I = 1, K
CYCLE(1) = CYCLE (NCY + 1)
K = LT - NCY + 1
DO 3 I = K, LT
```

```
3     CYCLE(I) = CYCLEU (I+NCY-LT)
      NK = 0
1     RETURN
      END
```

The arguments and variables of SUBROUTINE CBOX2 are now defined:

CYCLE = the current historical data array being used by the model

CYCLEU = an array holding newly generated historical data to be used for updating CYCLE

LT = lenth of CYCLE

NCY = number of simulation cycles between updates

NK = index for counting simulation cycles since last update

CPT = current time point value of the variable for which CBOX2 has been called

c. APPLICATION OF GASP UTILITY ROUTINES

c. GENERAL OPERATING PATTERN OF THE PM SUBSECTOR SIMULATION MODEL

Thus far in this paper we have discussed only the basic structure of the PM subsector simulation model, and some specific techniques to be employed in the prediction mechanism. Some of the performance criterion which will be generated have been mentioned, but so far nothing has been said about the actual operation of the PM simulation model. It should become even more evident after this brief discussion of the operating pattern of the PM simulation model, that a very versatile and efficient information storage and retrieval system will have to be available in the simulation program. The basic steps in the operation of the PM model are listed below. Following this list, each step is described in brief detail.

1. Load historical price data.
2. Adjust price data to 1/40 year intervals.
3. Generate and store speculative future prices.
4. Smooth the speculative price profiles generated in 3 ($PPS_i \longrightarrow YP_i$) and store.
5. Generate and store speculative urban demand for foodgrains, SUD_i -- MT/yr
6. Generate and store speculative profit profiles, SFF_i — W/yr
   - along with -
   corresponding optimal holding times OTH_i — yrs
   - and -
   corresponding speculative urban demand, SUD_i — MT/yr
7. Begin simulation cycle.
8. Generate current PM demands and marketings to adjust inventory, $PDAI_i$ and PMAI — MT/yr

9. Store PM purchasing information, $PPUR_i$ — MT/yr
10. Continue simulation loop to next prediction phase.
11. Repeat prediction (speculative) phase and apply feedback correction factors.
12. Purge computer storage files.
13. Continue above pattern to end of simulation run.

1. Load historical price data

The simulation model will begin with a set 4 years of historical time-series price data for the period 1966-1969.

2. Adjust price data to 1/40 year intervals

It will be preferable to have time-series price data available at intervals of .025 years (1/40 year — one DT) or finer. Whatever the sampling rate, however, the data will be transformed into .025 year intervals to make it compatible with the KASSIM model. A technique for making this transformation has been described Section B.5.a. of this paper.

3. Generate and store speculative future prices

Using the above price data, various statistics will be calculated: a regression line through the data representing the 'price trend line' for each commodity (PTL_i); weighted average deviations from the PTL for corresponding periods during the year ($ADPTL_i$); autocorrelation between deviations of price from the PTL with a lag of one DT ($ACDP_i$); and standard deviation of price deviations from the PTL (SDP_i). These statistics are then used as the parameters in the stochastic model of equation (15) for predicting producer prices (PPS_i) at intervals of one DT for approximately 2 years into the future. If we assume a constant marketing margin between producer and consumer prices, then future expected selling prices (PSS_i) can be generated from corresponding predicted purchasing prices by the simple relationship of equation (33). All predicted price profiles should be stored for later reference.

4. Smooth the speculative price profile generated in 3 above ($PPS_i \longrightarrow YP_i$)

Since the speculative profit profile PFF_i is generated from a stochastic model, it can be expected to have a fair amount of random variation or 'noise'. The smoothing operation will enable us to work more easily with each profile, but as with all simplifying manuevers we will <u>lose</u> information in the process. At this stage of development, both the raw and smoothed profiles will be stored for later reference. Techniques for smoothing the price profiles are described in Section B.2.a.2) of this paper.

5. Generate and store speculative urban demand for foodgrains, SUD_i — MT/yr

PM purchasing patterns will be based on inventory stockpiles at the time of purchase, expected disappearance rates, and the optimal holding times. Since there is expected to be a close correlation between seasonal urban consumption patterns and commodity prices, these projections will be based on speculative prices calculated and recorded in 4 above. It is expected that a linear regression model relating expected urban consumption rates to speculative commodity selling prices, per capita income, and a set of seasonal dummy variables will suffice for the present.

6. Generate and store speculative profit profiles, SFF_i — W/yr
   - along with -
   corresponding optimal holding times, OTH_i — yrs
   - and -
   corresponding speculative urban demand, SUD_i — MT/yr

Given the above predictions of future prices, along with interest rates and associated storage costs, it is possible to generate a speculative profit profile (SFF_i), representing the maximum profits realizable from purchases made over the upcoming year. Corresponding to each entry of SFF_i is an optimal holding time OTH_i and a speculated urban demand SUD_i. A method for generating the speculative profit profiles with optimal holding times and corresponding urban demand has been discussed in detail in Section B.2.b.3) of this paper. Again, all the above information should be stored for later reference.

7. BEGIN THE SIMULATION CYCLE

Steps 2 thru 6 above might be termed the "speculation phase" of the PM simulation model. With the above information ready for easy retrieval, storage, and discharge (when no longer useful), we are ready to begin the simulation cycle. The above steps are repeated periodically throughout the simulation run. Price data will be updated 4 times each simulation year. With a simulation cycle time increment of DT=.025 year, this will mean revising predictions every 10 simulation cycles.

8. Generate current PM demands and marketings to adjust inventory, $PDAI_i$ and $PMAI_i$ — MT/yr

Given the inventory stock level at the time of purchase, the expected disappearance rate profile, and the optimal holding time for purchases during the current time period, it is possible to calculate the level and timing of purchase and sales required to maximize the expected profits. This will be the private marketing demand to adjust inventory, $PDAI_i$ -- MT/yr. Private marketing purchases, $PPUR_i$ -- MT/yr, will correspond to $PDAI_i$ (unlagged) unless, of course, there is insufficient supply available. A procedure for generating PM speculative demands and marketings has been described in Section B.3.c.2) of this paper.

9. STORE PM PURCHASING INFORMATION, $PPUR_i$ -- MT/yr

As indicated in 8 above, the actual PM purchases are not determined in the PM subsector model — only the PM demand to adjust inventory, $PDAI_i$ -- MT/yr. A sudden burst of PM demand for rice, say, during the early summer months may not meet with an adequate supply available for sale. The government may also be competing to make purchase at the same time in which case rationing will take place in the transactions. The jump in demand will force producer prices to rise, in turn causing more rice to go on the market from farm storage.

The above paragraph is oversimplified and tends to force us to 'get ahead of ourselves.' The main point to convey here is that private marketing purchases, $PPUR_i$, are determined <u>outside</u> the PM subsector and, in actuality, are inputs to the PM subsector model. The following purchasing information is now appropriately stored.

1. Current simulation cycle index counter number, NTIME -- #.
2. Amount purchased during this particular time period, $PPUR_i(t)*DT$ -- MT
3. Level of PM inventory after current purchases and sales, $PINV_i(t)$ -- MT
4. Rate of current urban demand UD_i -- MT/yr
5. Actual producer and consumer prices, $P_i(t)$ and $CPU_i(t)$ -- W/MT

10. CONTINUE SIMULATION LOOP TO NEXT PREDICTION PHASE

Steps and 8 and 9 are repeated each simulation cycle. In addition more bookkeeping is required. We assume a FIFO disappearance pattern of PM inventory. As the simulation run progresses and the initial PM inventory is exhausted from the first time-cell

(T-C), future PM sales are supplied from successive T-C's. The "oldest" T-C still containing inventory will furnish the supply which is marketed at any particular time. When a T-C is depleted of inventory, the actual holding time of the purchases made in that T-C is recorded, If more than one time period is required to exhaust the purchases made in a certain T-C, then the average holding time is recorded. If a T-C does not contain enough inventory to satisfy current urban demand, it is exhausted, actual holding time recorded, and the next successive T-C is moved into position of satisfying the remainder of current non-farm demand. If and when there are no predecessor time-cells holding inventory (purchases) then $PINV_i(t)$ is necessarily zero and urban demand cannot be satisfied. In this case $PSLS_i(t) = 0$.

11. Repeat prediction (speculation) phase and apply feedback correction factors

As indicated in 7 above, the speculation phase are repeated periodically throughout the simulation run. Price data (loaded in step 1 above) are "merged" with output price data from the simulation run to this point. All price data are, of course, "aged" appropriately. Most recent price output data become the newest "historical" data. The oldest data are then discharged. Evaluation of the projection results can be accomplished by making use of the T-C information "held" for this purpose.

Correction factors can then be applied to the prediction mechanism. Correction factors are briefly discussed in Section B.4.b. of this paper.

12. Purge computer storage files

When T-C information is outdated or is no longer of use it is cleared from the computer. These T-C's can now be used for new information.

13. Continue above pattern to end of simulation run

D. MODIFICATIONS IN EXISTING KASSIM COMPONENTS

In order to effectively interface the GM simulation model with the existing KASSIM model, some refinements and modifications are necessary in the farm production component (PRODN) and the urban demand component (DEMAND). These components are described in Appendix A of the KASS report and again in the User's Manual (Special Report No. 9).

The production component (PRODN) can be run in a fine-time mode, and with proper timing is capable of generating credible seasonal labor profiles. However, the farm consumption, farm storage, and sales from farm storage behavioral mechanisms must be refined. Farm consumption is currently based on average annual prices. Price and income elasticities are also based on yearly averages and do not necessarily hold valid information about the short-run seasonal farm consumption response. An accurate farm sales behavioral function has not yet been incorporated into the production component. Currently, this function is merely a constant proportion of farm storage "available for sale."

The urban demand component currently does not operate in the fine-time mode. Again, income and price elasticities, used to parameterize the model, are based on average annual responses and do not necessarily hold valid information about the short-run seasonal urban consumption response to changes in income and p[illegible]s.

Dr. Moon, Pal Yong, of the Korean Development Institute has been investigating some of the seasonal foodgrain demands and marketings in Korea.[1/] A review of the econometric model used in Dr. Moon's study has indicated that, with some minor adjustments and "re-assumptions", it can be fully incorporated into the KASSIM model. Although the model was not originally developed for prediction purposes, it seems capable of generating credible seasonal responses for farm consumption, farm sales, and urban demand. This will give us a significant head start in refining the KASSIM model to account for seasonal farm/urban foodgrain demand and marketing behavior. Of course, independent research into these response patterns should be undertaken to verify the applicability of the Moon model in this context.

Dr. Moon's model consists of 8 simultaneous equations; 6 behavioral equations and 2 market clearing identities. The 6 behavioral equations describe the seasonal farm demand, farm sales, and urban consumption demand for rice and barley in Korea. The 2 market clearing identities were included to complete the above system. Since TSLS was used to estimate the above coefficients, the market identities have no effect on the estimation of the six behavioral equations.

[1/] Moon, Pal Yong, An Econometric Analysis of Foodgrain Demand and Marketings; Partial v.s. Total Response Analysis, Korea Development Institute, Seoul, Korea, 1972.

If we replace the 2 static market equilibrium identities in the above system by the (yet to be described) dynamic relationships between prices and excess demands, the above model is transformed from a static system of simultaneous equations into a dynamic system of recursive equations.

Moon's system of seasonal response equations are given on the following page. Notice that in the farm sales and urban demand equations, prices are the only endogenous variables appearing on the rhs. If in the KASSIM model, prices at time t are calculated based on prices and excess demands at time t-DT, we have, by definition, a reduced form for endogenous prices at time t. The values of prices at time t can then be used in the farm sales and urban demand equations to obtain a reduced form for farm sales and urban demand at time t. Finally, values of prices and farm sales at time t can be used in the farm demand equations to obtain a reduced form for farm demand at time t.

Information needed to incorporate Moon's seasonal response model directly into the KASSIM model is given in Appendix B. The raw data used to estimate the original Moon model is also included for later reference if desired.

E. FURTHER DEVELOPMENT

Moon's Seasonal Response Model

(Farm Demand)

$$q_R^{FD} = b_{10} + b_{11}P_R + b_{12}D_1P_R + b_{13}D_2P_R + b_{14}P_B + b_{15}P_W$$
$$+ b_{16}q_{Rt-1}^{FK} + b_{17}(P_Rq_R^{FS} + P_Bq_B^{FS} + Y_{NRB}) + b_{18}D_1 + b_{19}D_2$$

$$q_B^{FD} = b_{20} + b_{21}P_B + b_{22}D_1P_B + b_{23}D_3P_B + b_{24}P_R + b_{25}P_W$$
$$+ b_{26}q_{Bt-1}^{FK} + b_{27}(P_Rq_R^{FS} + P_Bq_B^{FS} + Y_{NRB}) - b_{28}D_1 + b_{29}D_3$$

(Farm Sales)

$$q_R^{FS} = b_{30} + b_{31}P_R + b_{32}D_1P_R + b_{33}D_2P_R + b_{34}L_{t-1} + b_{35}E$$
$$+ b_{36}q_{Rt-1}^{FK} + b_{37}(P_Rq_{Rt-1}^{FK} + P_Bq_{Bt-1}^{FK} + Y_{NRB}) + b_{38}D_1 + b_{39}D_2$$

$$q_B^{FS} = b_{40} + b_{41}P_B + b_{42}D_1P_B + b_{43}D_3P_B + b_{44}L_{t-1} + b_{45}E$$
$$+ b_{46}q_{Bt-1}^{FK} + b_{47}(P_Rq_{Rk-1}^{FK} + P_Bq_{Bt-1}^{FK} + Y_{NRB}) + b_{48}D_1 + b_{49}D_3$$

(Urban Demand)

$$q_R^{UD} = b_{50} + b_{51}P_R + b_{52}D_1P_R + b_{53}D_2P_R + b_{54}P_B + b_{55}P_W$$
$$+ b_{56}P_RY_U + b_{57}Y_U + b_{58}D_1 + b_{59}D_2$$

$$q_B^{UD} = b_{60} + b_{61}P_B + b_{62}D_1P_B + b_{63}D_3P_B + b_{64}P_R + b_{65}P_W$$
$$+ b_{66}P_BY_U + b_{67}Y_U + b_{68}D_1 + b_{69}D_3$$

Variable Definitions for Moon's Model[1/]

Endogenous Variables:

q_R^{FD} = farm per capita consumption of rice — kg/#-mo

q_B^{FD} = " " " " barley — kg/#-mo

q_R^{FS} = farm per capita sales of rice — kg/#-mo

q_B^{FS} = " " " " barley — kg/#-mo

q_R^{UD} = urban per capita consumption of rice — kg/#-mo

q_B^{UD} = " " " " barley — kg/#-mo

P_R = monthly average wholesale price of rice deflated by the index of nongrain wholesale prices WPI_n — W/kg

P_B = monthly average wholesale price of barley deflated by WPI_n' — W/kg

Exogenous Variables:

P_W = monthly average wholesale price of wheat flour deflated by WPI_n — W/22 kg (bag)

q_{Rt-1}^{FK} = farm per capita stock of rice at end of previous month -- kg/#

q_{Bt-1}^{FK} = farm per capita stock of barley at end of previous month — kg/#

Y_{NRB} = farm per capita income originating from non-rice-barley sources deflated by index of prices paid by farmers (PPFI) — W/#-mo

---

1/ *The original coefficients of Moon's model have been transformed so that KASS units of measure can be used. The units indicated here are the original units.*

Variable Definitions (cont'd)

L_{t-1} = farm per capita liabilities as of the end of the previou month deflated by PPFI -- W/#

E = farm per capita cash expenditures for clothing, educati etc., deflated by PPFI -- W/#-mo

Y_U = urban per capita disposable income deflated by the inde of urban consumer prices -- W/#-mo

D_1 = 1 if October - January period
= 0 otherwise

D_2 = 1 if February - May period
= 0 otherwise

D_3 = 1 if June - September period
= 0 otherwise

APPENDIX A

Private Marketing Subsector Variables

(w/o Speculation)

Private Marketing Subsector Variables

$A1_i$ -- W/MT-yr	Storage and handlding costs
$A2_i$ -- W/MT-yr	Storage capacity costs
$A3_i$ -- W/MT	Selling cost
$A4_i$ -- W/MT	Acquisition cost
AP_i -- W/yr	Current PM profitability on sales
$AVCHPI_i$ -- W/MT-yr	Average variable cost of holding inventory
CPU_i -- W/MT	Consumer prices
CS_i -- W/yr	Cost of selling
$FCHPI_i$ -- W/yr	Fixed costs of holding private inventory
INT -- Percent/yr	Interest rate
MM_i -- Percent	Marketing margin
P_i -- W/MT	Producer prices
PCAP -- MT	Current PM Capacity
$PDAI_i$ -- MT/yr	PM demand to adjust inventory
PDF_i -- Percent	Proportion direct farm sales
$PINV_i$ -- MT	PM stockpiles
$PMDEM_i$ -- MT/yr	Total PM demand
$PMLOSS_i$ -- %/yr	Private marketing losses
PMP_i -- W/yr	PM profit
$PPUR_i$ -- MT/yr	PM purchases

Private Marketing Subsector Variables Cont'd

$PSLS_i$ -- MT/yr	PM sales
$TCHPI_i$ -- W/yr	Total cost of holding PM inventory
$TEXP_i$ -- W/yr	Total PM commodity expenditures
TPINV -- MT	Total PM stockpile
TPMP -- W/yr	Total PM profit
TREVP -- W/yr	Total PM revenue
$TTEXP_i$ -- W/yr	Total PM expenditures
Q_i -- MT/yr	Consumer demand
QP_i -- MT/yr	PM demand to satisfy urban consumption
$REVP_i$ -- W/yr	PM revenue
$VCHPI_i$ -- W/yr	Variable costs of holding private inventory

APPENDIX B

Adjusted Coefficients for Seasonal Response Model

Coefficient	Original Coefficient Value	X	Transformation Factor	=	New Coefficient Value
b_{10}	19.71818		12E-3		.2366182
b_{11}	-.37891		12E-6		-.45469E-5
b_{12}	.19285		"		-.23142E-5
b_{13}	.09112		"		.1093E-5
b_{14}	.28441		"		.34129E-5
b_{15}	.00504		12/22E-6		.605E-7
b_{16}	.00041		12		.49E-2
b_{17}	-5.83402		E-3		-.583402E-2
b_{18}	-2.29762		12E-3		-.275714E-1
b_{19}	-.00584		"		-.701E-4
b_{20}	4.4200		12E-3		.53040E-1
b_{21}	-.02975		12E-6		-.3570E-6
b_{22}	-.01780		"		-.2136E-6
b_{23}	.26391		"		.31669E-5
b_{24}	.01967		"		.23604E-6
b_{25}	.04160		12/22E-6		.4992E-6
b_{26}	-.00199		12		-.2388E-1
b_{27}	-.08842		E-3		-.8842E-4
b_{28}	-5.42871		12E-3		-.651445E-1
b_{29}	.00194		"		.2328E-4

Coefficient	Original Coefficient Value	X	Transformation Factor	=	New Coefficient Value
b_{30}	-16.42861		12E-3		-.1971433
b_{31}	.10343		12E-6		.12412E-5
b_{32}	-.06336		"		-.7603E-6
b_{33}	.02841		"		.3409E-6
b_{34}	.00662		12E-3		.794E-4
b_{35}	.01020		E-3		.1020E-4
b_{36}	.07998		12		.9597
b_{37}	-.00072		E-3		-.72E-6
b_{38}	5.86913		12E-3		.704295E-1
b_{39}	-1.15583		"		-.138610E-1
b_{40}	.56981		12E-3		.68269E-2
b_{41}	.01763		12E-6		.2116E-6
b_{42}	-.00508		"		.609E-7
b_{43}	-.01446		"		-.1735E-6
b_{44}	.00023		12E-3		.28E-5
b_{45}	-.00479		E-3		.479E-5
b_{46}	.03720		12		.4464
b_{47}	.00018		E-3		.18E-6
b_{48}	-.03374		12E-3		.4049E-3
b_{49}	1.21469		"		.145763E-1

Coefficient	Original Coefficient Value	X	Transformation Value	=	New Coefficient Value
b_{50}	28.84979		12E-3		.3461974
b_{51}	-.40033		12E-6		-.48040E-5
b_{52}	.10238		"		.12286E-5
b_{53}	.67135		"		.80562E-5
b_{54}	.05579		"		.66948E-6
b_{55}	.000056		12/22E-6		.67E-9
b_{56}	-.00172		E-6		-.172E-8
b_{57}	-.00663		E-3		-.663E-5
b_{58}	-4.08876		12E-3		-.490651E-1
b_{59}	-2.69047		"		-.322856E-1
b_{60}	5.86330		12E-3		.703596E-1
b_{61}	-.20029		12E-6		-.24034E-5
b_{62}	-.03494		"		-.4192E-6
b_{63}	.10288		"		.12346E-5
b_{64}	.13043		"		.15652E-5
b_{65}	.000019		12/22E-6		.23E-9
b_{66}	-.00135		E-6		-.135E-8
b_{67}	-.00232		E-3		-.232E-5
b_{68}	.85843		12E-3		.10301E-1
b_{69}	-2.57700		"		-.309240E-1

UNIT ANALYSIS OF COEFFICIENT TRANSFORMATIONS

Coefs	Orig Var	New Var	Original Coefficient	X	Coefficient Transform	=	New Coefficient	X	New Var	=	New Term
b_{10}/b_{20}	1	1	$\frac{\text{kg}}{\#\text{-mo}}$		$\frac{\text{MT}}{\text{kg}}\ \frac{\text{mo}}{\text{yr}}$		$\frac{\text{MT}}{\#\text{-yr}}$		1		$\frac{\text{MT}}{\#\text{-yr}}$
b_{11}/b_{21}	$\frac{\text{w}}{\text{kg}}$	$\frac{\text{w}}{\text{MT}}$	$\frac{\text{kg}}{\#\text{-mo}}\ \frac{\text{kg}}{\text{w}}$		$\frac{\text{MT}}{\text{kg}}\ \frac{\text{MT}}{\text{kg}}\ \frac{\text{mo}}{\text{yr}}$		$\frac{\text{MT}}{\#\text{-yr}}\ \frac{\text{MT}}{\text{w}}$		$\frac{\text{w}}{\text{MT}}$		$\frac{\text{MT}}{\#\text{-yr}}$
b_{12}/b_{22}	"	"	"		"		"		"		"
b_{13}/b_{23}	"	"	"		"		"		"		"
b_{14}/b_{24}	"	"	"		"		"		"		"
b_{15}/b_{25}	$\frac{\text{w}}{\text{22kg}}$	$\frac{\text{w}}{\text{MT}}$	$\frac{\text{kg}}{\#\text{-mo}}\ \frac{\text{22kg}}{\text{w}}$		$\frac{\text{MT}}{\text{kg}}\ \frac{\text{MT}}{\text{kg}}\ \frac{\text{mo}}{\text{yr}}\ \frac{1}{22}$		$\frac{\text{MT}}{\#\text{-yr}}\ \frac{\text{MT}}{\text{w}}$		$\frac{\text{w}}{\text{MT}}$		$\frac{\text{MT}}{\#\text{-yr}}$
b_{16}/b_{26}	$\frac{\text{kg}}{\#}$	$\frac{\text{MT}}{\#}$	$\frac{\text{kg}}{\#\text{-mo}}\ \frac{\#}{\text{kg}}$		$\frac{\text{mo}}{\text{yr}}$		$\frac{1}{\text{yr}}$		$\frac{\text{MT}}{\#}$		$\frac{\text{MT}}{\#\text{-yr}}$
b_{17}/b_{27}	$\frac{\text{w}}{\#\text{-mo}}$	$\frac{\text{w}}{\#\text{-yr}}$	$\frac{\text{kg}}{\#\text{-mo}}\ \frac{\#\text{-mo}}{\text{w}}$		$\frac{\text{MT}}{\text{kg}}$		$\frac{\text{MT}}{\text{w}}$		$\frac{\text{w}}{\#\text{-yr}}$		$\frac{\text{MT}}{\#\text{-yr}}$
b_{18}/b_{28}	1	1	$\frac{\text{kg}}{\#\text{-mo}}$		$\frac{\text{MT}}{\text{kg}}\ \frac{\text{mo}}{\text{yr}}$		$\frac{\text{MT}}{\#\text{-yr}}$		1		$\frac{\text{MT}}{\#\text{-yr}}$
b_{19}/b_{29}	"	"	"		"		"		"		"

UNIT ANALYSIS OF COEFFICIENT TRANSFORMATIONS

Coefs	Orig Var	New Var	Original Coefficient	X	Coefficient Transform	=	New Coefficient	New Var	New Term
b_{30}/b_{40}	1	1	$\frac{\text{kg}}{\#\text{-mo}}$		$\frac{\text{MT}}{\text{kg}} \cdot \frac{\text{mo}}{\text{yr}}$		$\frac{\text{MT}}{\#\text{-yr}}$	1	$\frac{\text{MT}}{\#\text{-yr}}$
b_{31}/b_{41}	$\frac{\text{w}}{\text{kg}}$	$\frac{\text{w}}{\text{MT}}$	$\frac{\text{kg}}{\#\text{-mo}} \quad \frac{\text{kg}}{\text{w}}$		$\frac{\text{MT}}{\text{kg}} \quad \frac{\text{MT}}{\text{kg}} \cdot \frac{\text{mo}}{\text{yr}}$		$\frac{\text{MT}}{\#\text{-yr}} \quad \frac{\text{MT}}{\text{w}}$	$\frac{\text{w}}{\text{MT}}$	$\frac{\text{MT}}{\#\text{-yr}}$
b_{32}/b_{42}	"	"	"		"		"	"	"
b_{33}/b_{43}	"	"	"		"		"	"	"
b_{34}/b_{44}	$\frac{\text{w}}{\#}$	$\frac{\text{w}}{\#}$	$\frac{\text{kg}}{\#\text{-mo}} \quad \frac{\#}{\text{w}}$		$\frac{\text{MT}}{\text{kg}} \quad \frac{\text{mo}}{\text{yr}}$		$\frac{\text{MT}}{\#\text{-yr}} \quad \frac{\#}{\text{w}}$	$\frac{\text{w}}{\#}$	$\frac{\text{MT}}{\#\text{-yr}}$
b_{35}/b_{45}	$\frac{\text{w}}{\#\text{-mo}}$	$\frac{\text{w}}{\#\text{-yr}}$	$\frac{\text{kg}}{\#\text{-mo}} \quad \frac{\#\text{-mo}}{\text{w}}$		$\frac{\text{MT}}{\text{kg}}$		$\frac{\text{MT}}{\text{w}}$	$\frac{\text{w}}{\#\text{-yr}}$	$\frac{\text{MT}}{\#\text{-yr}}$
b_{36}/b_{46}	$\frac{\text{kg}}{\#}$	$\frac{\text{MT}}{\#}$	$\frac{\text{kg}}{\#\text{-mo}} \quad \frac{\#}{\text{kg}}$		$\frac{\text{mo}}{\text{yr}}$		$\frac{1}{\text{yr}}$	$\frac{\text{MT}}{\#}$	$\frac{\text{MT}}{\#\text{-yr}}$
b_{37}/b_{47}	$\frac{\text{w}}{\#\text{-mo}}$	$\frac{\text{w}}{\#\text{-yr}}$	$\frac{\text{kg}}{\#\text{-mo}} \quad \frac{\#\text{-mo}}{\text{w}}$		$\frac{\text{MT}}{\text{kg}}$		$\frac{\text{MT}}{\text{w}}$	$\frac{\text{w}}{\#\text{-yr}}$	$\frac{\text{MT}}{\#\text{-yr}}$
b_{38}/b_{48}	1	1	$\frac{\text{kg}}{\#\text{-mo}}$		$\frac{\text{MT}}{\text{kg}} \quad \frac{\text{mo}}{\text{yr}}$		$\frac{\text{MT}}{\#\text{-mo}}$	1	$\frac{\text{MT}}{\#\text{-yr}}$
b_{39}/b_{49}	"	"	"		"		"	"	"

Coefs	Orig Var	New Var	Original Coefficient ·	X Coefficient Transform	= New Coefficient	New Var	New Term
b_{50}/b_{60}	1	1	$\frac{kg}{\# - mo}$	$\frac{MT}{kg}$ $\frac{mo}{yr}$	$\frac{MT}{\#-yr}$	1	$\frac{MT}{\#-yr}$
b_{51}/b_{61}	$\frac{w}{kg}$	$\frac{w}{MT}$	$\frac{kg}{\# - mo}$ $\frac{kg}{w}$	$\frac{MT}{kg}$ $\frac{MT}{kg}$ $\frac{mo}{yr}$	$\frac{MT}{\#-yr}$ $\frac{MT}{w}$	$\frac{w}{MT}$	$\frac{MT}{\#-yr}$
b_{52}/b_{62}	"	"	"	"	"	"	"
b_{53}/b_{63}	"	"	"	"	"	"	"
b_{54}/b_{64}	"	"	"	"	"	"	"
b_{55}/b_{65}	$\frac{w}{22kg}$	$\frac{w}{MT}$	$\frac{kg}{\#-mo}$ $\frac{22kg}{w}$	$\frac{MT}{kg}$ $\frac{MT}{kg}$ $\frac{mo}{yr}$ $\frac{1}{22}$	$\frac{MT}{\#-yr}$ $\frac{MT}{w}$	$\frac{w}{MT}$	$\frac{MT}{\#-yr}$
b_{56}/b_{66}	$\frac{w}{kg}$ $\frac{w}{\#-mo}$	$\frac{w}{MT}$ $\frac{w}{\#-yr}$	$\frac{kg}{\#-mo}$ $\frac{kg}{w}$ $\frac{\#-mo}{w}$	$\frac{MT}{kg}$ $\frac{MT}{kg}$	$\frac{MT}{\#-yr}$ $\frac{MT}{w}$ $\frac{\#-yr}{w}$	$\frac{w}{MT}$ $\frac{w}{\#-yr}$	$\frac{MT}{\#-yr}$
b_{57}/b_{67}	$\frac{w}{\#-mo}$	$\frac{w}{\#-yr}$	$\frac{kg}{\#-mo}$ $\frac{\#-mo}{w}$	$\frac{MT}{kg}$	$\frac{MT}{\#-yr}$ $\frac{\#-yr}{w}$	$\frac{w}{\#-yr}$	$\frac{MT}{\#-yr}$
b_{58}/b_{68}	1	1	$\frac{kg}{\#-mo}$	$\frac{MT}{kg}$ $\frac{mo}{yr}$	$\frac{MT}{\#-yr}$	1	$\frac{MT}{\#-yr}$
b_{59}/b_{69}	"	"	"	"	"	"	"